Revealed Preference Differences Among Credit Rating Agencies

A thesis submitted to the University of Manchester for the degree of Doctor of Philosophy (PhD) in the Faculty of Humanities

2012

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Total Word Count: 73,594

List of Abbreviations

CAPM	Capital Asset Pricing Model
cdf	Cumulative Distribution Function
CRAs	Credit Rating Agencies
DCR	Duff and Phelps Credit Rating Agency
DD	Distance to Default
EJR	Egan Jones Ratings Company
Fitch	Fitch IBCA
GDP	Gross Domestic Product
GICS	Global Industry Classification Standard
G-Index	Governance Score suggested by Gompers et al. (2003)
GMM	Generalized Method of Moments
IOSCO	International Organization of Security Commissions
KMV	Kealhofer, McQuown and Vasicek
K-S Test	Kolmogorov Smirnov Test
LGD	Loss Given Default
Moody's	Moody's Investor Services
MPD_t	Market Implied Probability of Default
MDA	Multiple Discriminant Approach
NBER	National Bureau of Economic Research
NRSRO	Nationally Recognized Statistical Rating Organization
PD	Probability of Default
Regulation FD	Regulation Fair Disclosure
RPD_t	Rating Implied Probability of Default
S&P	Standard and Poor's Rating Services
SEC	Securities and Exchange Commission

Abstract

The University of Manchester
Waseem Noor Larik
Doctor of Philosophy (PhD)
May 2012
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The thesis studies the factors which underpin the allocation of credit ratings by the two major credit rating agencies (CRAs) namely Moody's and S&P. CRAs make regular headlines, and their rating's judgements are closely followed and debated by the financial community. Indeed, criticism of these agencies emerged, both in this community and the popular press, following the 2007-2008 financial crisis. This thesis examines several aspects of the allocation of credit ratings by the major agencies, particularly in relation to (i) their revealed "loss function" preference structure, (ii) the determinants underpinning the allocation of credit ratings and (iii) the reasons determining the circumstances when the two agencies appear to differ in their opinions, and we witness a split credit rating allocation.

The first essay empirically estimates the loss function preferences of two agencies by analyzing instances of split credit ratings assigned to corporate issuers. Our dataset utilises a time series of nineteen years (1991-2009) of historical credit ratings data from corporate issuers. The methodology consists of estimating rating judgment differences by deducting the rating implied probability of default from the estimated market implied probability of default. Then, utilising judgment differences, we adapt the GMM estimation following Elliott et al. (2005), to extract the loss function preferences of the two agencies. The estimated preferences show a higher degree of asymmetry in the case of Moody's, and we find strong evidence of conservatism (relative to the market) in industry sectors other than financials and utilities. S&P exhibits loss function asymmetry in both the utility and financial sectors, whereas in other sectors we find strong evidence of symmetric preferences relative to those of the market.

The second essay compares the impact of financial, governance and other variables (in an attempt to capture various subjective elements) in determining issuer credit ratings between the two major CRAs. Utilising a sample of 5192 firm-year observations from S&P400, S&P500 and S&P600 index constituent issuer firms, we employ an ordered probit model on a panel dataset spanning 1995 through 2009. The empirical results suggest that the agencies indeed differ on the level of importance they attach to each variable. We conclude that financial information remains the most significant factor in the attribution of credit ratings for both the agencies. We find no significant improvement in the predictive power of credit rating when we incorporate governance related variables. Our other factors show strong evidence of continuing stringent standards, reputational concerns, and differences in standards during economic crises by the two rating agencies.

The third essay investigates the factors determining the allocation of different (split) credit ratings to the same firm by the two agencies. We use financial, governance and other factors in an attempt to capture various subjective elements to explain split credit ratings. The study uses a two-stage bivariate probit estimation method. We use a sample of 5238 firm-year observations from S&P 500, S&P 400, and S&P 600 index constituent firms. Our results indicate that a firm having greater size, favourable coverage and higher profitability are less likely to have a split. However, smaller firms with unfavourable coverage and lower profitability appear to be rated lower by Moody's in comparison to S&P. Our findings suggest that the stage of the business cycle plays no significant role in deciding splits, but rating shopping and the introduction of regulation FD increase the likelihood of splits arising.

Declaration

I, Waseem Noor Larik declare that no portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of Learning.

Copyright Statement

Dedication

To my parents

To my wife, Sameen

Acknowledgements

I would like to thank my supervisor Prof. Michael Bowe for his tremendous support, guidance and invaluable comments in structuring this thesis. I truly feel, it is an honour to have worked with Prof. Michael Bowe. He has encouraged me to have my own research ideas, and provided me with the direction necessary to complete this thesis, particularly in difficult times. I would also like to thank Dr. George Christodoulakis for his support and guidance during my first empirical chapter, and for providing me an opportunity to initiate my PhD studies at Manchester Business School.

I would also like to thank the other members of the internal PhD committee to which I regularly presented my progress and research ideas. In particular, I would like to thank Prof. Stuart Hyde and Dr. Alex Taylor for their valuable comments during PhD committee meetings. I would also like to thank Dr. Konstantinos Stathopoulos for his help and discussion on corporate governance related issues in this thesis. I have also presented working paper versions of my chapter 2 and 3 in conferences, and I would like to thank and acknowledge participants and organizers of the following conferences. Manchester Business School Doctoral Conference 2009, Manchester, U.K., Academy of Business Conference (ABR) 2011, New Orleans, U.S.A., and British Accounting and Finance Association (BAFA) 2012, Brighton, U.K. Special thanks to Randall Valentine, Antonios Siganos, and Owain Gwilym for their helpful discussion and comments during conference presentations.

During my PhD research, I also discussed my research related queries on specific topics from distinguished academic and industry professionals through emails. These include, Prof. Edward I. Altman (NYU), Prof. Anthony Saunders (NYU), Prof. Michael Brennan (UCLA), Prof. A.C. MacKinlay (UPenn), Richard Cantor (Moody's), Christopher Mann (Moody's), Pedro Gomes (ECB), and Philip Rother (ECB). I am thankful for their suggestions on technical issues related to the research topic.

I would also like to thank Government of Pakistan for the award of Masters leading to PhD scholarship, and State Bank of Pakistan (SBP) for allowing me to pursue higher academic studies abroad. Last but not the least, I would like to thank my family for being always a great help, without their support and motivation this would not have been possible.

Chapter 1

Introduction

1.1 Motivation

Credit rating agencies (henceforth CRAs), in the form they exist today, were first established in the U.S. by John Moody in 1909 (Partnoy (1999)). In today's financial markets, credit ratings underpin the very structure and fabric of the financial marketplace. Strauss (2002) terms credit ratings the risk language that we all speak and rely on. The overriding aim of credit ratings is to reduce information asymmetries among different market participants. Bond issuers are aware that the allocated ratings affect their financing costs. Similarly, investors and lenders make informed investment and lending decisions by using credit rating information. The regulatory use of credit rating information in the current financial markets further enhances the role of CRAs. These uses encourage bond issuers to seek credit ratings from multiple CRAs in order to ascertain their cost of debt, fulfil regulatory requirements and enhance investment opportunities.

An important factor in CRAs business is the judgement concerning the likelihood of timely payments from the issuers. CRAs make regular headlines and are closely followed by the financial community. The famous corporate debacles of Enron and WorldCom raise several questions concerning the judgement of these CRAs, while the financial crisis of 2007-2008 further exacerbated these criticisms. CRAs traditionally generated their revenues by selling credit rating information to investors. However, in the early 1970s, the major agencies changed their business model from an "investor pay" to an "issuer pay" model. Cantor and Packer (1994) cite the emergence of low cost copiers at that time to this change, as investors paying for the rating services were further disseminating rating information to other investors for free. This change of business model complemented this free flow of information, but enhanced criticism of the CRAs business model due to the "inherent conflict of interest" arising from this process.

The criticism of CRAs in terms of their perceived inability to accurately predict economic crises and corporate failures have instigated several actions by the relevant authorities. In July 2011, the U.S. Congress passed the Dodd-Frank Act and stated that during 2007-08 financial crisis, CRAs had contributed significantly to the mismanagement of risks by financial institutions and investors[1]. Subsequent to the promulgation of Dodd-Frank Act, SEC proposed several actions targeting CRAs in two dimensions. First, these proposals directly target CRAs business structures in order to prevent inherent conflicts of interest and enhance internal controls. Second, SEC plans to reduce the reliance on CRA information by reducing the scope of existing regulatory uses of CRA information. These plans include changing existing rules related to money market funds and removing references to credit ratings from broker-dealer and other financial responsibility rules[2]. Similar actions are also proposed by the European Commission to enhance rating credibility and reduce the reliance on CRA information[3].

These actions by the regulatory authorities validate the criticism of CRAs to some extent. Similarly, certain recent literature also analyses conflicts of interests in the CRA business. For instance, Jiang et al. (2011) examines changes in bond ratings surrounding the date when S&P began to adopt the issuer-pays business model. They find that S&P increased its rating levels once it switched to collecting fees from issuers. Similarly, Becker and Milbourn (2010) argue that the increased competition from the third largest CRA, Fitch, resulted in more issuer friendly ratings from Moody's and S&P. More recently, Bolton et al. (2012) finds that CRAs are more prone to inflate ratings in booms than in recessions, and argue that due to criticism CRAs have become more cautious in recessions. This evidence further validates general criticism and undermines the use of credit rating information by market participants. However, Blume et al. (1998) finds CRAs are consistently becoming more stringent and Covitz and Harrison (2003) provide evidence that reputational concerns are causing CRAs to respond to these general criticisms. Cheng and Neamtiu (2009) find CRAs have improved the timeliness and

[1]Text of the Dodd-Frank Act (Wall Street Reform and Consumer Protection Act) is available on the SEC website: http://www.sec.gov/about/laws/wallstreetreform-cpa.pdf

[2]Text of "SEC proposes rules to increase transparency and improve integrity of credit rating" is available: http://www.sec.gov/news/press/2011/2011-113.htm

[3]Text and actions by the European Commission are available: http://ec.europa.eu/internal_market/securities.htm

accuracy of rating actions after major corporate debacles such as Enron and WorldCom. This suggests that CRAs are well aware of the criticisms targeting their behaviour, and are consistently improving their methodologies and rating standards.

The above-mentioned actions by the regulatory authorities and the evidence in the literature motivate this further study of CRAs. In this thesis, we attempt to study the rating allocation decisions of two agencies namely Moody's and S&P. We study this in terms of their "loss function" preferences, rating determinants and difference of opinion on the creditworthiness of the same issuer. In the first essay (chapter 2), we estimate the loss function preferences of the two major agencies and link these preferences with the different incentives facing CRAs. To the best of our knowledge, this essay is the first study to empirically estimate the loss function preferences among CRAs, and as such this constitutes its major contribution. In the second essay (chapter 3), we attempt to study the impact of financial, governance and other factors in determining the credit ratings allocated by the two agencies. In this study, we contribute in terms of determining the role of non-financial factors in explaining credit ratings. The third essay (chapter 4) examines the factors predicting the likelihood of split credit ratings between the two major agencies. This essay makes one key contribution to the current literature on split credit ratings, in the sense that we do not limit our findings on the factors determining likelihood of splits, but we further contribute by analysing the factors that determine whether one agency is likely to issue lower ratings than the other within a split. Such information is potentially of great use to corporations seeking credit ratings from one of the two major agencies.

The rest of chapter 1 is organized as follows: First, we present the institutional background of CRA business and briefly introduce Moody's and S&P. Second, we briefly introduce each empirical chapter. Finally, we present the structure of the thesis.

1.2 Institutional Background

CRAs are organizations that rate the creditworthiness of a sovereign country, specific company or financial product, such as a debt security or a money market instrument. The Credit Rating Agency Reform Act promulgated in 2006 provides the SEC with the authority to establish a registration and oversight program for NRSRO. The SEC first applied the NRSRO designation to CRAs in 1975[4], and currently there are 10 CRAs with the status of a NRSRO. Langohr and Langohr (2008) differentiate CRAs on the type of coverage (geography, industry, issuer or instruments), methodology (statistical modelling or fundamental credit analysis), pricing model (issuer fee or investor subscription), type of scale (ordinal with actual PD or cardinal with estimates of relative default probabilities), and size. The three dominant players in the U.S. CRA industry, suggesting the existence of an oligopolistic market structure, are: Moody's, S&P and Fitch. The most striking fact about the industry is that over 80%[5] of all rated issues outstanding are provided by just two CRAs namely Moody's and S&P, with the third, Fitch having 14% of market share. The three major CRAs follow an "issuer-pay model" with their credit assessment relying upon the quantitative and qualitative judgement of their credit analysts. We briefly introduce our two major agencies used in this thesis empirical analysis, namely Moody's and S&P in the following paragraphs.

S&P refers to Standard and Poor's Credit Market Services, responsible for its credit rating business. S&P's parent company is McGraw-Hill, which provides financial services related to equities, and independent equity and mutual fund research. S&P also provides valuation advisory services, credit analysis, and investor education and data services through its subsidiary, Capital IQ. The agency's history traces back almost a century. Poor's Publishing Company issued its first ratings guide in 1916. Standard Statistics Company published its first ratings in 1922, and the two companies merged to form S&P in 1941. The McGraw-Hill Companies acquired S&P in 1966. In S&P's word's "a credit rating is its 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 (2009)). S&P currently has a 22 long-term rating-point scale, with AAA as the highest, and D being the lowest rating. In 1974, by adding + and -, S&P introduced the notch system to its (then) existing 10 rating categories. This introduction of the notch system further classifies an issuer firm or a bond issue at the high end or the low end of a rating category. We attach

[4] In 1975, SEC first used the term NRSRO in referring to agencies whose credit ratings could be used to determine net capital requirements for broker-dealers (Cantor and Packer (1994)).

[5] Langohr, H., and P. Langohr, (2008), "The Rating Agencies and their Credit Ratings: What they are, How they Work and Why they are Relevant", Wiley Finance Publications, England.

rating definitions of the two rating agencies as Appendix I and II, while a table comparing long-term rating scales among three major CRAs as appendix III of this thesis.

John Moody’s (1868-1958) laid the foundations in 1909 for Moody’s Investors Services. Moody’s was incorporated in 1914, and by 1924 it covered nearly 100% of the U.S. bond market. Currently Moody’s is a subsidiary of Dun and Bradsteet, which purchased the rating agency in 1962. Moody's defines credit ratings as "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 (2009)). Moody’s currently has 21 long-term rating-point scales, with Aaa as the highest, and C being the lowest. In 1983, Moody’s introduced a notch system (rating modifiers) by adding 1 and 2 to their rating categories. The only substantive difference in long-term rating scales between S&P and Moody’s is that S&P assigns D ratings to a firm or an issuer when it defaults, whereas ratings are removed from a defaulted firm in the case of Moody’s.

1.3 Research Focus and Contributions

The thesis conducts three essays on the properties of the two major agencies, Moody’s and S&P, in terms of their loss function preferences, rating determinants and factors underlying rating splits. In the following sections, we briefly introduce the three empirical essays by explaining the focus and contributions to the literature of each essay.

1.3.1 Loss Function Estimation

The first essay (chapter 2) empirically determines the loss function preferences between the two major CRAs, in an attempt to reveal whether there exists tangible differences across agencies relating to the asymmetry/symmetry of the estimated loss functions. The economic implications of an incorrect rating judgment of the PD by a rating agency can result in the imposition of heavy costs (and potential benefits) to its end users. The issuer pay model followed by the two major agencies raises questions concerning the incentives of CRAs to exhibit preferential behaviour towards its fee-paying clientele. Becker and Milbourn (2011) propose that optimistic preferences exist among the two agencies, as they find evidence of rating inflation in response to the entrance of the third rating agency, Fitch. Beaver et al. (2006) argue that CRAs focusing only on the concerns of investors may exhibit a somewhat symmetric loss function, as they will evidence similar responses and concerns towards rating upgrades and downgrades. Finally, the regulatory use of credit rating information raises reputational issues for the agencies. These regulatory requirements and concerns with potential loss of reputation may suggest that CRAs will have an asymmetric loss function, as these requirements and concerns provide them with incentives to be more conservative (Watts (2003)).

The above-mentioned uses of credit rating information ascertain different shapes for loss function preferences. To the best of our knowledge there is no single study which estimates the loss function preferences for the credit rating industry. We track historical credit ratings on issuers possessing credit ratings from both Moody's and S&P. These histories are obtained from two indices, the S&P 400, and S&P 600. Using a sample of nineteen years starting in 1991 through 2009, we define the rating judgment error as the MPD_t (market implied PD) minus the RPD_t (rating implied PD for both the agencies). We convert credit rating history into numeric numbers by using default studies of S&P to represent RPD_t, while we use the Merton (1974) model to estimate MPD_t following the Vassalou and Xing (2004) methodology. Using a time series data of these rating judgement errors for each issuer, we estimate loss function parameter following the Elliott et al. (2005) methodology. This method is applicable in situations in which we have a sample of time-series data, but the underlying model is unknown. We further conduct statistical and cross-sectional tests to understand differences both within and between CRAs.

Our results from the first essay suggest a systematic asymmetry of loss function preferences in the case of Moody's, whereas we find evidence of symmetric loss function estimates for S&P. Our use of rationality tests under various assumptions further validates our findings. Following Beaver et al. (2006) and Watts (2003), we associate Moody's conservative preferences with the regulatory use of credit ratings. On the contrary, S&P symmetric evidence of loss function is associated with its incentives to provide timely information to investors and to exhibit neutral preferences. Further cross-sectional analyses we conduct finds evidence of optimistic preferences by the two agencies towards the financial and utility sector issuers. This evidence of inherent asymmetry suggests that the two agencies have somewhat laxer standards towards financial and utility sector firms, and under-predict the associated risk relative to the market

To the best of our knowledge, this essay is the first study to empirically estimate loss function preferences within CRAs. Beaver et al. (2006) investigate the rating change timeliness of two agencies Moody's and EGR, and finds evidence of conservative behaviour from Moody's as compared to the other agency, EGR. We supplement Beaver et al.'s (2006) findings in three directions: First we estimate loss function preferences for the first time in the credit rating setting; second we provide evidence Moody's is not conservative across all industry sectors; finally, we provide evidence that the conservative preferences associated with Moody's cannot be generalized across all NRSRO. Cheng and Neamtiu (2009) find that CRAs have improved the timeliness and accuracy of their rating actions after major corporate debacles. However, our findings suggest these are not applicable to the utility and financial sectors and we provide evidence of somewhat laxer standards and under-prediction of the PD in these two sectors.

1.3.2 Credit Rating Determinants

The second essay (chapter 3) attempts to study the impact of financial, governance and other factors in determining credit ratings given by Moody's and S&P. There is a large literature which uses financial and accounting based information in order to determine credit ratings[6]. However, an attempt to associate other, non-financial factors with the allocation of credit ratings only becomes noticeable in more recent literature. Bhojraj and Sengupta (2003) and Ashbaugh et al. (2006) supplement the use of financial factors with governance related variables. Similarly, Blume et al. (1998) uses year-dummies along with the financial variables to determine credit ratings. Amato and Furfine (2004) use variables capturing the macroeconomic state of the economy along with financial variables to determine credit ratings. The studies using financial variables only generally fail to predict higher rated issuers, and possible reason given for this is the subjective element in differentiating between high rating categories. This motivate us to use factors

[6] See for instance, Horrigan (1966), West (1970), Pogue and Soldofsky (1969), Pinches and Mingo (1973 and 1975), Altman and Katz (1976), and Kaplan and Urwitz (1979)

other than financial variables in determining credit ratings, especially after the criticism of CRAs subsequent to high profile corporate failures such as Enron and WorldCom and the financial crisis of 2007-2008.

In this second essay, we aim to develop a relationship between the variables already shown to have explanatory power in the current literature, and also to incorporate additional variables that capture more subjective elements of the decision making process in rating assignment. We focus exclusively on two major agencies S&P and Moody's, and use their rating transitions data for each issuer spanning a period 1995 through 2009. Our final sample consists is of 5192 firm-year observations from S&P 400, S&P 500 and S&P 600 index constituent issuer firms. We use maximum likelihood estimation methods using an ordered probit model to associate ordered credit ratings with selected explanatory variables, and we use the percentage of correct predictions as a measure of the goodness-of-fit of our model. This allows us to compare three models; the first model uses only financial variables, the second adds governance variables and the third adds three other variables to capture subjective elements in ratings.

The results of the second essay suggest that the agencies indeed differ on the basis of the level of importance they attach to certain variables when allocating credit ratings. We find that financial information relating to an issuer such as coverage, leverage, profitability and market beta remains a significant factor in determining issuer credit ratings. The study finds no significant improvement in prediction rates subsequent to adding our three governance related variables. This may suggest that information conveyed by governance is already adequately captured by financial variables. However, our selected proxies designed to highlight general criticisms and the potential subjectivity of rating assignment processes significantly improve rating predictions. Moreover, this improvement in prediction accuracy is particularly significant in the case of the more highly-rated issuers which the existing literature is the least able to predict.

The essay extends the current literature on rating determinants in various directions. To our knowledge this is the first study to compare and combine financial, governance and other factors when analysing the determination of credit ratings. Governance has previously been associated with credit ratings in terms of its individual significance in explaining credit ratings, however to our knowledge its effect in terms of the improvement in predictive power obtained by adding governance related variables has not been addressed by the current literature. We also incorporate a set of new variables as proxies to examine the relationship between credit ratings in an attempt to quantify the criticism and subjectivity involved in the rating process. Previous studies fail to predict high rating category firms, and this study extends the previous literature by providing considerable improvement in the prediction success rate for firms occupying the higher rating categories.

1.3.3 Credit Rating Splits

The third essay (chapter 4) examines the factors determining the likelihood of split credit ratings between S&P and Moody's. The essay has two main themes. First, can we determine the reasons lying behind the likelihood of one agency allocating a lower rating than the other. This is achieved by estimating a bivariate probit estimation method utilising a set of variables found to have explanatory power in determining credit ratings. This method allows us to observe the likelihood of splits in the first stage, and further the likelihood of one agency rating lower within a sample of split credit ratings. Ederington (1986) does not find any consistent trend within split ratings, and concludes that the split ratings are caused by random errors. Morgan (2002) argues split ratings are due to asset opacity, and that financial firms which have more opaque assets, are more likely to have split ratings. However, Livingstone et al. (2007) shows there is a degree of persistence in split ratings, as in their sample about two thirds of initially split-rated bonds remain split-rated four years of rating transitions. This suggests split ratings are not due to random errors, but there is a difference of opinion by the agencies on the credit assessment of an issuer or an issue.

The second major theme of this essay is to determine differences between the notch level and category level splits. Approximately 20% of the U.S. corporate bond issues have category or letter level[7] split ratings, and about 50% of sub-ratings or notch-level[8] ratings are splits (see for instance, Ederington (1986), Livingston and Jewell (1998)).

[7] When AA is different from A and AAA, but not from AA+ and AA-.

[8] When AA is different from AA+ and AA-,

Becker and Milbourn (2011) find evidence of rating inflation by Moody's and S&P in reply to increased competition and entrance of the third largest rating agency, Fitch. We also examine splits at the notch and category level, by estimating two separate bivariate probit models using splits at the notch and category level as dependent variables.

The results of this third essay reveal that in terms of splits at the notch level, smaller firms having unfavourable coverage and profitability ratios are more likely to have splits. We find evidence that Moody's is more conservative in relation to a firm's (poor) financial profile, resulting in a split. In terms of governance related variables, S&P and Moody's both have congruent ratings in relation to a firm having higher management control vis-à-vis shareholder rights. However, Moody's places more value upon board independence and places firms with higher board independence in a high ratings category as compared to S&P. This results in S&P placing firms lower within a split. We also incorporate certain additional variables and find that the business cycle plays no significant role in the likelihood of observing a split. However, rating shopping and other subjective factors determining credit ratings play a role in the likelihood of splits. In terms of splits at the notch and category level, we find that firm's leverage level differences, along with other financial variables, play a role in category level splits. However neither rating shopping behaviour nor the percentage of institutional investment has any significant impact on the likelihood of observing splits at the category level.

This essay contributes to the current literature on split credit ratings in various dimensions. One key contribution is that we do not limit our findings to the factors determining the likelihood of splits, but we further contribute in terms of factors that determine whether one agency will allocate a lower rating than the other. Ederington (1986) concludes that split ratings are caused by random errors. Morgan (2002) finds split ratings are due to asset opacity, and Livingstone et al. (2007) shows that there is a degree of persistence in split ratings. Morgan (2002) also finds the split ratings are lopsided, with Moody's consistently on the downside. These findings suggest split ratings are caused by fundamental differences in interpretation of an issuer's credit profile, and we identify certain factors that determine conservative and optimistic behaviour of these two agencies. A second contribution is that we do not limit the factors we incorporate to determine splits only to financial variables, but we also include governance and other subjective elements to observe their impact on the likelihood of splits. We also contribute by providing evidence that different underlying factors explain notch and category level splits.

1.4 Thesis Structure

The thesis format follows the Alternative Format Thesis of the University of Manchester by incorporating different essays on related themes into a single thesis. This thesis consists of three self-contained essays, which are presented in chapter 2, 3 and 4. Each chapter has a separate literature review, answers unique and original research questions, to some extent exploits different datasets (although in chapters 2 and 3, we use almost identical datasets), and adopts different methodologies according to the research questions analysed. This implies that each empirical chapter makes a separate contribution to the literature.

The remainder of this thesis is organized as follows. Chapter 2 presents the first essay where we estimate the loss function preferences among the two major CRAs Moody's and S&P. The second essay is presented in chapter 3, where we examine the factors determining credit ratings between Moody's and S&P. Chapter 4 investigates the factors underpinning split credit ratings between S&P and Moody's. Finally, chapter 5 provides a summary of the major findings from each empirical chapter, and suggests some directions for further research.

Chapter 2

Revealed Preferences of Credit Rating Agencies from Split Credit Ratings

Summary

The study empirically analyzes instances of split credit ratings assigned to corporate issuers by Moody's and S&P. The objective is to estimate these agencies "loss function" preferences in assigning credit ratings. There is a literature on the different incentives faced by CRAs in allocating credit ratings; however, there is no study to the best of our knowledge attempting to identify the loss function preferences of CRAs. Our data set constitutes of a time series of nineteen years (1991-2009) of historical credit ratings data. We use issuer credit ratings history of S&P 400 and S&P 600 constituent firms for our analysis. From a methodological point of view, the study proceeds in two stages: Initially, we estimate market implied probability of default (MPD_t) using the Merton (1974) model following the Vassalou and Xing (2004) refinement of this methodology. We estimate rating judgment differences by deducting the rating implied probability of default (RPD_t) from the estimated MPD_t. Then, using judgment differences from our first stage, we adapt the GMM estimation along the lines of Elliott et al. (2005) to extract the rating agencies loss functions. Our findings indicate both the agencies differ in their preferences while assigning issuer credit ratings. The estimated preferences show a higher degree of asymmetry in the case of Moody's, where we find strong evidence of conservatism (relative to the market) in industry sectors other than financials and utilities. S&P shows loss function asymmetry in both the utility and financial sectors, whereas in other sectors we find strong evidence of symmetric preferences. Further investigations reveal both the agencies appear to follow a higher degree of asymmetry in the case of financial and utility sector firms, as we observe optimistic preferences from both the agencies.

2.1 Introduction

Investors need information relating to both their potential and current investments to make informed investment decisions. These informed decisions require in-depth analysis of investment opportunities and involve heavy costs of information acquisition. To bridge the information gap and avoid costs, CRAs act as information intermediaries between investors and issuers. The main function of a credit rating agency is to issue an independent assessment of corporate (and sovereign) creditworthiness, encapsulated in a judgment concerning the likelihood that investors will receive payments of interest and principal. Investors in the financial markets do not have timely access to the same set of information, and credit ratings represent one potential solution to the issue of asymmetric information (Ramakrishnan and Thakor (1984)). Cowan (1991) terms the judgment delivered by a rating agency is an attempt to summarize the confidential and publicly available information. However, the abrupt downgrading of Enron and WorldCom only after problems occurred raised questions concerning the credibility of CRAs. The financial crisis of 2007-2008 further exacerbated the criticism, as abrupt and unanticipated credit rating downgrades of a number of participants and securities in the structured credit markets led to large market losses and a rapid drying up of liquidity (Sy (2009)).

The economic implications of an incorrect rating judgment of the PD can impose heavy costs to its end-users. Subsequent to developments in the financial markets, the use of credit rating information has also increased, as rating information is not only used by issuers and investors, but also by market participants under regulatory[9] and contractual requirements. The SEC reports that at least 44[10] of its rules and forms currently incorporate reference to agency ratings. Similarly banks are required under Basel II to use credit rating information for capital calculations. Under contractual arrangements, debt covenants require credit rating information, where a downgrade below investment grade from a NRSRO can violate company debt covenants. These regulatory uses of

[9] A series of governmental regulations effectively gave the credit rating agencies a quasi-governmental role. These started in the year 1975 when SEC introduced Rule 15c3-1, which required broker-dealer firms to calculate net capital requirements using the credit rating assigned by an approved group (NRSRO) of CRAs (Beaver et al. (2006)).

[10] See for instance, Christopher Cox Statement on proposal to increase investor protection by reducing reliance on Credit Ratings, June 25, 2008.

rating agencies force issuers to seek ratings from multiple rating agencies. These regulatory requirements suggest that a rating agency will have an asymmetric loss function, as the regulations generate incentives to be more conservative (Watts (2003)). The reputation cost of being overly optimistic can be very costly to the rating agency, as any evidence of rating inflation may instigate actions from regulatory bodies to prohibit investors from using rating information from a certain agency, for example losing NRSRO status from the SEC.

Major agencies such as Moody's and S&P follow an "issuer pay"[11] model. Corporate issuers of bonds and structured finance products pay a fee to receive a credit rating. The business of CRAs is dependent upon these fee payments what under are made contractual arrangements between issuers and CRAs. The conservative or asymmetric loss function can be costly to issuers as it involves higher interest payments on its debt obligations. The induced lowering of credit ratings can also force issuers to seek multiple ratings, and avoid certain agencies perceived to have more stringent standards. Becker and Milbourn (2011) find evidence of rating inflation by Moody's and S&P in reply to increased competition and entrance of the third largest rating agency Fitch.

The main function of a rating agency is to become intermediary between investors and bond issuers by providing one solution to certain problems generated by asymmetric information. Investors use CRAs for valuation purposes. The correct valuations require timely actions by CRAs in response to any good or bad news. Any delay in actions by the rating agency can be costly to investors. Beaver et al. (2006) suggests that rating agencies focusing only on investors may exhibit a more symmetric loss function, suggesting a similar response and concern towards rating upgrades and downgrades. However, investors cannot observe the level of effort the intermediary puts into costly information acquisition and processing, which some have suggested provides more incentives to rating agencies putting too little effort into rating (Gorton and Winton (2003)). Similarly, contractual portfolio composition imposed on mutual funds, pension funds and foreign reserves held by the central banks are limited to investment-grade assets. Any abrupt changes by the CRAs can cause heavy costs to these users due to

[11]The major change for the rating industry came in the early 1970s, when the industry changed its business model from the "investors pay" model to an "issuers pay" model.

portfolio repositioning and rebalancing, and can raise compliance issues. Similarly, CRAs also provide ancillary services to different clients, including investment management firms and financial institutions in relation to the management of credit and other risks. These ancillary services require credit rating information input, suggesting more incentives to CRAs to provide timely actions on good and bad news, as it may increase their market share in these ancillary services. These incentives generate different shape of loss functions for rating agencies, and also suggest asymmetry/symmetry can cause costs to these end users in different dimensions.

The above-mentioned uses of ratings in different situations generate different shapes of rating agencies loss function. However, to the best of our knowledge there is no single study estimating loss function preferences in the credit rating industry. This empirical chapter investigates loss function preferences, by studying the two major CRAs Moody's and S&P. We estimate loss function parameters following the Elliott et al. (2005) methodology, as this method is applicable in situations where we have the time-series data, but the underlying model is unknown. Using a sample of nineteen years starting 1991 through 2009, we define our rating judgment error as MPD_t (market implied probability of default) minus the RPD_t (rating implied probability of default). We use the Merton (1974) model to estimate MPD_t following Vassalou and Xing's (2004) methodology. We aim to ascertain loss function preferences between the two agencies by accounting for rating splits[12] between two agencies on the assessment of PD. Specifically, we aim to answer following research questions: Does an analysis of split ratings and a comparison of ratings judgment errors signify a fundamental disagreement between Moody's and S&P about the estimates of the PD? What is the shape of the loss function preference of Moody's and S&P, implied by the rating judgment error? What does this reveal about the preference structure of Moody's and S&P? Are there any differences in default judgments across different sectors between the two rating agencies?

To summarize our findings, our results suggest Moody's is more conservative than S&P. Beaver et al. (2006) document that regulatory and contractual needs force NRSRO firms to generally be conservative. We supplement Beaver et al.'s (2006) findings in three

[12] Credit rating disagreement between two agencies on a single issue or issuer is termed as a split rating.

directions: First we estimate loss function preferences for the first time in the context of credit rating settings; second we provide evidence Moody's is not conservative across every industry sector, as the agency appears to follow optimistic preferences in the financial and utility sectors; Last we provide evidence that the conservative preferences associated with Moody's cannot be generalized across all NRSRO, as we document a more symmetric preference structure from S&P. We associate S&P having symmetric preferences with its higher incentives to be more investor friendly and become efficient input information for its ancillary services. However, we find more lax standards towards financial and utility sectors issuers resulting in under-estimation of PD by both the agencies. Cheng and Neamtiu (2009) find CRAs have improved timeliness and rating accuracy after major corporate debacles; however these findings are not applicable to the utility and financial sectors, and we provide evidence of lax standards in these two sectors.

The organization of the remainder of the chapter 2 is as follows: Section 2.2 provides a literature review, section 2.3 describes the sources and definition of data utilized and also presents the methodology, Section 2.4 describes the empirical results and discusses the findings and economic significance of our results. Finally section 2.5 concludes the study.

2.2 Literature Review

Credit ratings from the two major agencies Moody's and S&P are mostly congruent. However, we observe the two agencies as having differences of opinion resulting in a split credit rating on the same issuer or debt security. Billingsley et al. (1985) and Ederington (1986) observe 14% splits at a category level[13]. After the introduction of the notch system[14], split ratings increase to almost 50% (see for instance Cantor et al. (1997) and Perry et al. (1988)). Split credit ratings bring new information to the market. Moreover, information differences are persistent. Livingston et al. (2008) report over

[13] For instance, when AA is different from A or AAA, but same as AA- or AA+ is termed as a category level split.

[14] Moody's introduced notch level credit ratings in the year 1983, while S&P started notch level credit ratings in the year 1974. By introducing notch level modifications, rating categories are further divided into plus and minus symbols in case of S&P and numbers 1 and 2 to Moody's to show relative strength.

half of the time the two rating agencies maintain their relative assessment of assigned credit ratings even after four years of initial issuance. These systematic divergent opinions are a reflection of rating agency's loss function preferences. Depending upon the use of credit rating information, this asymmetry of its loss function can be costly to its end users. To the best of our knowledge, there is no single study investigating the shape of CRAs loss function. However, we find literature on the market reactions to split credit ratings, and rating agencies perceived loss function depending upon its mandate and incentives. We first discuss the empirical evidence on market reaction to split credit ratings, and then we evaluate the literature relating to the role of asymmetry in credit rating agencies loss function.

2.2.1 Split Ratings and Bond Yields

Billingsley et al. (1985) study the behaviour of bond reoffering yields in the presence of split ratings at a category level. In particular, they study two hypotheses: First, the divergence of agency opinion, and second, whether investors place greater confidence in one agency over another. Using least squares estimation methods, the authors conclude that the reoffering yields on split-rated bonds are not significantly different from the yields on the lower of the two split ratings. They find significant differences in yields compared to the higher rating yields. They conclude that the markets are cautious over split rated bonds and consider the lower of two ratings as a true representative of PD. Similarly, Perry et al. (1988) and Liu and Moore (1987) use splits at the notch level and study their impact on bond yields. They conclude that the impact on interest yields of a split rating of one rating class difference under an unmodified (category level) rating system is higher than that of a split rating of one level difference under the notch system. These studies conclude that bond yields with split ratings, investors consider the lower of the two ratings as a truer representative of the PD. This initial research evidence on the market reaction to split ratings suggests that investors do not have a preferred rating agency. However, they exhibit risk aversion as they consider the lower of the two splits as more representative of the PD.

This initial literature on the relationship of bond yields and divergence of opinion between two rating agencies suggests that split ratings increase the cost of debt of an issuer. If the true representative PD is the higher of the two ratings, then issuers of these securities have to pay a higher interest cost on their outstanding debt securities. On the contrary, Cantor et al. (1997) state that the empirical bond pricing models only use ratings issued by S&P or Moody's, but not both. The data sample they use consists of 4399 bond issues between 1983-1993 that have ratings from both the S& P and Moody's. Their empirical findings reveal that pricing models that rely on Moody's or S&P's ratings (but not both) produce unbiased but highly inefficient estimates. They state that the best prediction results occur when yields are inferred from the equally weighted combination of the two ratings. For investment-grade split ratings, investors take a more conservative view, by relying more on the lower of the two. However, in below investment grade, an average of the two split ratings produces more accurate and efficient results. They conclude that investors in below investment grade sector apparently take a less conservative view of split ratings and rely on the average bond yields. These findings are in line with the findings of both Livingston and Jewell (1998) and Hseuh and Kidwell (1988), who conclude that the average of the two ratings determine the bond yields asset by the market. These studies suggest market strongly reacts to these split rated bonds, and places issues having split ratings under a separate credit quality different from higher or lower of a split.

Livingston and Zhou (2010) study the asset opacity associated with split rated bonds, and find that investors consider bonds having split ratings as a separate credit category. Their results reveal that on average, the yield on a split rated bond is 7 basis points higher than that of non split rated bonds of similar credit risk. This yield premium increases from 5 basis points for one-notch splits to 20 basis points for three-notch splits. These studies suggest that the splits between the two major agencies convey additional information to the market. Earlier studies on the relationship of bond yields and split ratings suggest that markets' take a more conservative position on split ratings. Later studies suggest that split rated bonds are considered as a separate credit category and yields are determined by the average of the higher and lower of split ratings. If we analyze these splits from an issuer side, we find that issuers are at advantage as well as a disadvantage from having multiple ratings. If the true PD is represented by the lower of the two ratings in a split, issuers bear lower interest cost due to these multiple ratings.

Similarly, they pay higher interest cost on debt securities where the true representative PD is higher rating within a split, as investors take the average of two ratings.

2.2.2 Rating Agencies Preferences and Incentives

These market reactions suggest that CRAs preferences towards conservatism and optimism generate market reactions. These divergent opinions serve different end users of these ratings in a different way. In an "issuer pay model", an issuer not satisfied with its allocated rating by a rating agency can ask for further ratings to reduce its cost of capital. Similarly, an agency being too lax is assigning lower credit ratings underestimates the true PD and can cause losses to investors. Credit ratings used for regulatory purposes force agencies to be more conservative; similarly, investors need rating actions by the agencies to make informed investment decisions. These divergent incentives faced by agencies can cause them to exhibit an asymmetric loss function. Currently to the best of our knowledge, there is no study investigating the form of the loss function revealed by CRAS. In this section, we discuss the existing available literature on the various incentives to have an asymmetric loss function.

Conservatism in accounting standards is defined as a differential verifiability required for recognition of profits versus losses (Watts (2003)). In the credit ratings scenario, conservatism requires that agencies require more convincing evidence of good than bad news. This conservative approach entails that the loss function of a rating agency will exhibit asymmetry. This asymmetry of its loss function identifies the rating agency's preferences and incentives towards its clients. Beaver et al. (2006) studies the behaviour of certified[15] versus non-certified[16] bond rating agencies. They use Moody's as a representative of certified agencies, and EJR as a non-certified representative[17]. They argue that the properties of the ratings issued by CRAs are dependent upon the end users or clients of these credit ratings. They identify the two major uses of ratings are in contracting and valuation. These uses establish the CRAs incentives to have an asymmetric and symmetric loss function to satisfy their client needs in the following

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[15] Beaver et al. (2006) use certified agencies for NRSRO status holders from SEC.

[16] Non-Certified credit rating agencies are not recognized as NRSRO by SEC.

[17] One December 21, 2007 SEC granted NRSRO status to EJR.

way: Investors use credit ratings for valuation purposes; such valuation requires timely and effective actions by rating agencies on both good and bad news. The contractual use of credit ratings for compliance in bond portfolio eligibility and debt covenants often required by regulators, requires agencies to have a conservatism approach. They test three dimensions to observe differences in reaction of two agencies. (1) timeliness (across agencies); (2) asymmetric response to new information (within and across agencies); and (3) behaviour around the investment grade/non-investment grade cut off (across agencies). Their final sample consists of 1369 firm-year observations, and for consistency they use only those observations where both the CRAs provide ratings. Their Granger (1969) causality tests suggest EGR ratings are timelier compared to Moody's, while the findings on stock price movement suggest Moody's ratings appear to be more asymmetric as they do a better job of reflecting negative news than they do positive news. On the contrary, EGR appears to be symmetric in terms how they incorporate positive and negative news. Finally, they find Moody's downgrades to be slow at the critical investment and non-investment[18] grade segment. They conclude that certified agencies having their rating used in contracting are more conservative, while non-certified agencies are more focused towards their incentive to be symmetric in terms of their investment advisory role.

Beaver et al. (2006) study although ignores S&P another major agency, but their proxies to demonstrate timeliness and asymmetric reaction of Moody's towards good and bad news show rating conservatism rather than optimism. Conservatism associated with credit rating is not only limited to Moody's. Atilgan et al. (2008) study the behaviour of CRAs across two different set of firms. The study compares credit rating of U.S. domestic firms registered in the U.S. with the ratings of foreign firms listed in the U.S. This study provides a cross-sectional variation in rating conservatism and argues that the information asymmetry associated with foreign firms listed in the U.S. leads CRAs to be more conservative. To test the rating conservatism they use ratings at issuance as the dependent variable in an ordered probit regression. The sign on their Non-US issues is the variable of interest after controlling for issue and country-specific variables. They

[18] Any investment is termed as investment-grade, if its higher or equal to BBB- (Baa3) ratings, whereas any investment lower than equal to BB+ (Ba3) is termed as speculative or non-investment-grade.

use the initial rating assigned by three major agencies S&P, Moody's and Fitch as their dependent variable, and in case of splits they use the highest of three ratings. The final sample they adopt for the study consists of 4,204 public debt issues by non-U.S. firms (treatment sample) and 28,334 public debt issues by U.S. firms (control sample). Their results suggest that the rating agencies impose a significant downward bias when rating bonds cross-listed in the U.S. They report that these cross-listed firms are not only rated lower initially, but also suggest CRAs are less likely to upgrade these cross-listed issues. They conclude that these lower ratings are concentrated among investment grade cross-listed bonds, consistent with higher reputation costs involved in failing to predict the default of an investment grade bond. These results suggest information asymmetry in the case of limited information associated with foreign firms listed in the U.S is the main driving force towards rating conservatism.

The information asymmetry in terms of solicited[19] and unsolicited[20] credit ratings is studied by Poon (2003) and Poon and Firth (2005) in detail. Harrington (1997) states the practice of unsolicited lower ratings is equivalent to "financial blackmailing by CRAs", and it forces issuers to pay and initiate the rating process. However, alternative explanation of this financial blackmailing is the limited information associated with unsolicited ratings. In unsolicited ratings, credit agencies rely only on public information and in solicited ratings they have access to private information. Poon (2003) uses a pooled time-series cross-sectional data of 265 firms in 15 countries from S&P during 1998-2000 to study the relationship between solicited and unsolicited ratings. The study finds significant differences in the distribution of two rating types, the ratings associated with unsolicited ratings are lower compared to solicited ratings. However the paper concludes that these differences may be associated with differences in standards used for solicited and unsolicited ratings by the agency. Since, the study uses same set of financial information to determine solicited and unsolicited ratings by using ordered probit model, it is difficult to interpret private information hypothesis in this study. Poon and Firth (2005) using 1,060 ratings of 82 countries compare solicited and unsolicited

[19] Credit ratings issuance process, paid for and initiated by issuers is commonly known as "solicited ratings".

[20] Credit ratings not paid and initiated by issuers, and rated free of cost by the CRAs are known as "unsolicited ratings"

ratings, and find that solicited ratings are lower. They conclude that following the Golin (2001) findings, these may be due to the CRAs conservative approach towards the limited information available through public sources. This lack of information exhibits means a cautious attitude adopted by the CRA resulting in conservative approach; once they have access to private information they tend to be more optimistic.

Morgan (2002) investigates the pattern of disagreement (rating splits) between Moody's and S&P on 7,862 new bonds issued publicly by U.S. firms between January 1983 and July 1993. He hypothesizes disagreement between the two major agencies is more common due to asset opacity issue. His results reveal the agencies do indeed disagree more frequently and more widely over banks, possibly due to banks having opaque assets. This asset opaqueness creates a greater likelihood of disagreement between different analysts of these firms resulting in a split credit rating. He also reports that the behaviour of rating agencies is lopsided, where Moody's is more conservative compared to S&P. Haggard et al. (2006) examine whether firm opacity in the form of lower quality financial statements contributes towards agency disagreement. As financial statement are prepared in accordance with accounting principles and regulations, there exists an issue regarding the quality of these statements. This paper reveals that lower quality financial reporting contributes to information uncertainty, which in turn creates uncertainty in the relative risk assessment of rating agencies.

The literature mentioned above provides evidence of CRAs various approaches towards risk assessment of an issuer. However, there is also a growing literature providing evidence of the subsequent evolution of more stringent standards in ratings. Blume et al. (1998) study the behaviour of S&P credit ratings using a panel data from 1978 through 1995. They use year-dummies to observe the differences in rating standards across years using an ordered probit model. Their results suggest that a firm having a given level of financial variables in 1978, would likely be given a lower credit rating in subsequent years for the same level of financials. These results suggest that CRAs are becoming more stringent in assigning higher credit ratings, so effectively becoming more conservative. Cheng and Neamtiu (2009) study the response of NRSRO's to increased regulatory pressure and investor criticism over failure to predict high profile bankruptcies such as Enron and California Utilities. They report that lack of timeliness is the main reason behind criticism of rating agencies over failure to predict such high profile bankruptcies. However, they conclude that CRAs have improved their timeliness and rating accuracy in recent periods.

Covitz and Harrison (2003) also provide evidence of reputational concerns. They generate testable predictions regarding the anticipation of credit-rating downgrades by the bond market. Their findings strongly indicate that the rating changes do not appear to be influenced by inherent conflicts of interest, but rather, suggest rating agencies are motivated primarily by reputation-related incentives. The literature on rating conservatism and the continuing stringent standards set by the two agencies suggest the general criticism on rating agencies is improving timeliness and rating accuracy.

Becker and Milbourn (2011) study competition in the credit rating industry, and find evidence of rating inflation by Moody's and S&P in reply to increased competition and entrance of the third largest firm, Fitch. They report that the increasing market share of the third rating agency, Fitch, is pushing other two agencies Moody's and S&P to assign higher credit ratings to issues and issuers, resulting in credit rating inflation. They conclude that regulators recommendations to increase competition within rating industry to discourage oligopolistic market structure may benefit in terms of reducing associated rating fee and increase in information flow. However, it may impair the reputational concerns of CRAs and increase costs to investors by inducing lax rating processes. Similarly, Mathis et al. (2009) also study reputational concerns within the rating agency business in rating residential mortgage-backed securities (RMBS). They show that CRAs conservative attitude towards assessment of creditworthiness is dependent upon the fee structure. They are lax on rating products which constitute a major part of their corporate earnings and strict where the portion of fee is less. They conclude that CRAs have incentives to rate high due to the "issuer pay" model. This literature provides conflicting evidence on the incentives and preferences of CRAs. As such, there is a strong need to estimate the loss function preferences of agencies and a need to study cross-sectional differences in these preferences.

2.3 Data Description and Methodology

2.3.1 Data Sources

There are two main stages of the data collection: The first stage involves obtaining data to be used for estimation of market implied PD using the Merton (1974) model. The second stage involves data requirements to calculate the rating implied PD. The data collection process and data sources are explained below:

Market Implied Probability of Default (MPD_t)

We use time-series data to implement Merton's (1974) option pricing model. The data window is 1991-2009 for S&P 400 index constituent issuers, and 1994-2009[21] for S&P 600 index constituent issuers. Data is obtained from CRSP daily files, and is used for estimating the market value of the firm. Daily files provide the daily closing price of the firm's equity (PRC). We also collect the number of outstanding shares (SHROUT) from the same data source. The daily closing price and the number of outstanding shares are multiplied together to obtain the current market value of the firm, which is converted to millions of dollars in order to correspond to the data from the other source COMPUSTAT.

We use COMPUSTAT annual files to collect the data inputs for estimating the firm's debt value. We use the book values of "Debt in Current Liabilities" and "Long-term Debt" series for our sample of issuers for our data window, starting 1991 through 2009. Vassalou and Xing (2004) argue that long-term debt is important for two main reasons: First, issuers need to service their long-term debt and the interest payments constitute part of their short-term debt obligations. Second, the size of a firm's long-term debt burden affects the ability of a firm to roll over its short-term debt. We use the Vassalou and Xing (2004) method of including firm's half of the long-term debt into firm's short-term debt. The same method of adding half of long-term debt as part of short-term debt is applied by KMV[22]. We use the 1-year Treasury bill rate obtained from the Federal

[21] We encounter data limitation in terms of S&P 600 issuers, as the daily index movement for S&P 600 index is available only from the year 1994 onwards.

[22] KMV (Kealhofer, McQuown and Vasicek) is a trademark of KMV Corporation that was founded in 1989. The KMV model calculates the Expected Default Frequency (EDF) based on the firm's capital structure, the volatility of the assets returns and the current asset value.

Reserve Board Statistics as our measure of the risk-free rate, daily data for the date window of 1991-2009 is used for this purpose. We use index values as a proxy for the market return, and the Global Financial Database is used for the purpose of collecting daily index returns of both the indices: The S&P 400 and S&P 600. Daily index data for S&P 600 is available from 1994 onwards and for the S&P 400 index we do not have any data limitations.

Rating Implied Probability of Default (RPD_t)

Our sample consists of S&P 400[23] and S&P 600 index[24] constituent issuers having long-term rating assignments from Moody's and S&P. Following Beaver et al. (2006) method, we only select issuers having ratings from both S&P and Moody's, as it helps to compare two agencies. We use Bloomberg to collect long-term issuer ratings. We select only long-term ratings, as they are comparable on a single scale[25]. Following earlier discussion on data limitations, we collect data for S&P 400 index constituent issuers starting 1991 through 2009, and for S&P 600 issuers starting 1994 through 2009. Out of total sample of 1000 issuers, 356 or 35.6% have ratings from S&P. Out of these 356 issuers, 51 are not rated by Moody's. The final number of issuers in our portfolio is 303. However, further data restrictions limit us to present results based upon 263[26] issuers. In these presented 263 loss function alpha parameters for our sample of issuers firms, 85 (32%) come from S&P 600 index constituent issuers, and 178 (68%) from S&P 400 index.

We use annual default rates per rating category as a proxy for the RPD_t. Rating agencies do not publish any predicted forward-looking default rates for each rating category; we use these ex-post default rates as a proxy because these are based upon the

[23] The S&P MidCap 400 provides investors with a benchmark for mid-sized firms. The index covers over 7% of the U.S. equity market, and seeks to remain an accurate measure of mid-sized companies, reflecting the risk and return characteristics of the broader mid-cap universe on an on-going basis.

[24] The S&P SmallCap 600 covers approximately 3% of the domestic equities market. Measuring the small cap segment of the market that is typically renowned for poor trading liquidity and financial instability, the index is designed to be an efficient portfolio of companies that meet specific inclusion criteria to ensure that they are investable and financially viable.

[25] Long-term rating comparison among three major CRAs table is attached as appendix III of this thesis.

[26] In some cases, our GMM estimation method does not generate any meaningful number. There are two main reasons, behind this: First due to low frequency of time-series data, and second where we have zero estimated PD from both the estimated sources i.e. RPD_t and MPD_t.

whole universe of rated issues and issuers. In the case of S&P we use the "2009 Annual Global Corporate Default Study and Rating Transitions" report to extract the default frequencies. The table used from the report is entitled "Global Corporate Default Rates by Rating Modifier". The annual corporate default studies are published and updated each year by the rating agency. Moody's also publishes an annual "Corporate Default and Recovery Rates" report. Both the annual reports are available on the websites of the respective rating agency. We attach these default tables as appendix IV and V of this thesis. These numerical numbers presented in the appendices are the percentage of defaults over whole corporate universe rated by both the agencies. This way, the percentage shows the actual true defaults within each rating category. Hence, our measure of RPD_t represents the actual defaults in each rating category, and we use it as representative of rating implied probability of default.

Before we initiate our empirical estimations for the study, we compare the default tables of both the CRAs. We observe, out of total number of 459 (17 rating categories multiplied by the number of years, 1982-2009) comparable observations the two tables differ on 234 (51%) observations. The two tables are congruent over observations where we have default rate equal to zero, mostly linked to higher category issuers. This raises questions on the comparison, as our differences in tables may drive our loss function estimation preferences. We decide to use only S&P default tables to convert ratings from Moody's and S&P to a numerical RPD_t as representative of both the agencies. This allows us to capture the differences due to split ratings between two agencies, not due to differences in two tables. We prefer to use S&P over Moody's, as Moody's tables are based upon LGD rates, whereas S&P ratings convey the PD associated with the issuers.

Another important question arises here is of survivorship bias, as we only include current list of firms encompassing two indices S&P 400, and S&P 600. We select only those firms for our analysis that are rated by both the selected CRAs. We then trace back the rating history of those firms. Based on the rating history, we assign implied RPD_t to each rating. This PD rate is based upon the actual default frequency of firms in each rating category. If a company has a rating of AA- assigned by S&P, we assign this firm a PD based upon actual default frequency of all the firms in AA- universe, similarly we do the same for Moody's. In this way, we do not have survivorship bias, as the PD assigned to a current firm is based upon the defaults incurred by that rating category, not the actual implied PD of a particular firm.

2.3.2 Methodology

To address our research questions, our methodology incorporates two major steps which are explained below:

Step 1: Estimating Rating Judgment Error (MPD_t – RPD_t)

We initiate this first step by estimating the MPD_t. We follow the methodology proposed by Vassalou and Xing (2004) using the Merton (1974) option pricing model. The Vassalou and Xing (2004) methodology uses market data to compute the firm's MPD_t. Previous studies use historical accounting based approaches to estimate PD. However, market based approaches are inherently forward looking. Crosbie et al. (2003) argues that as market prices are the result of the combined willingness of many investors to buy and sell, variations in the market prices embody the synthesized views and forecasts of many investors. Most importantly, accounting based approaches do not take into consideration the volatility effect of market prices in calculating the firm's likelihood of default. Using accounting data, if the financial ratios between two issuers are similar, two firms may generate a similar PD. In contrast, in the case of market based approaches, while two firms may have the same levels of equity and debt, the firm with the higher equity price volatility is likely to have a higher PD. In our case, we do not argue for the superiority of one method over the other, but simply use the market based approach to compare the PD obtained from the two rating agencies, as it represents market sentiment in terms of the impact of share-price volatility.

As is standard in this literature, the firm's equity is analyzed as a call option on the firm's assets, as equity holders are residual claimants on the firm's assets after all other obligations are met. The strike price of the call option is the book value of the firm's liabilities. When the value of the firm's assets is less than its strike price, the value of equity is zero. This concept is utilized by KMV[27], where the asset price is determined through the share price. However, the method proposed by Vassalou and Xing (2004) differs from the KMV approach. There are two main reasons; first, KMV uses the empirical distribution of defaults, facilitated by access to a large dataset. For example in the KMV database, the number of firm-years of data is over 100,000, and includes more than 2,000 incidents of defaults. Secondly, the method of estimating DD in the two approaches also differs. KMV use the formula DD= (Market Value of Assets-Default Point)/(Market Value of Assets*Asset Volatility). In KMV the firm defaults when the value of the assets falls below the default point. In our case, a default occurs when the value of the assets of the firm is less than the value of the liabilities.

This is explained through equation (2.1):

$$\text{Value of Equity} = \text{Value of Assets} - \text{Value of Liabilities} \qquad (2.1)$$

If the firm equity value is negative, the claims of the creditors are not fully covered. The equity holders apply the walk- away principle, and creditors take over the firm. This stage is termed as a default situation. To understand Merton's (1974) model, we assume that firm's liabilities consist of just one zero-coupon bond with notional value L maturing in time T. As there are no payments until T, the equity holders will wait until time T, to decide whether to default or not. The PD is the probability that at time T the assets value is below the value of the liabilities.

To determine the firm's liabilities L, we use balance sheet data. We then specify the probability distribution of the asset value at maturity time, T. Here, we assume a log-normal distribution of financial assets i.e. the logarithm of asset value is normally distributed. Change in the per annum variance of the log asset value is denoted by σ^2. The expected per annum change in log assets value is denoted by $\mu - \sigma^2/2$, where μ is a drift parameter. Let t denote today, then the log asset value at maturity T follows a normal distribution and is given by equation (2.2):

[27] KMV (Kealhofer, McQuown and Vasicek) is now Part of Moody's Analytics Enterprise Risk Solutions. Moody's Analytics acquired KMV, a leading provider of quantitative credit analysis tools to lenders, investors, and corporations in 2002.

$$\ln A_T \approx N(\ln A_t + (\mu - \sigma^2/2)(T-t), \sigma^2(T-t)) \qquad (2.2)$$

Thus, if we know L, A_t, μ, σ^2", we can estimate firm's PD.

The probability that a normally distributed variable x falls below z is, $\Phi[(z \quad E[x]/\sigma(x)]$ where Φ denotes the cumulative standard normal distribution. If we apply probability expression to our case, we obtain expression given by equation (2.3).

$$\text{Prob (Default)} = \Phi\,[(\ln L - \ln A_t - (\mu - \sigma^2/2)(T-t))/(\sigma\sqrt{T-t})] \qquad (2.3)$$

Recall that the DD is simply the number of standard deviations that the firm is away from default. Thus, in our case, the DD measures the number of standard deviations the asset value A_T is away from default and is given by equation (2.4)

$$DD = (\ln A_t - \ln L + (\mu - \sigma^2/2)(T-t))/(\sigma\sqrt{T-t})$$
$$\text{Prob (Default)} = \Phi\,(-DD) \qquad (2.4)$$

where Φ is the cumulative standard normal distribution in the DD formula, there are two unobservable variables, the drift μ and the asset volatility σ. Here we follow option-pricing theory in specifying a relationship between the unobservable (A_t,σ) and observables. The current market value of the share price is used to calculate the asset value by multiplying the share price by the number of outstanding shares. As long as the asset value is below the value of liabilities, the value of equity is zero as all assets are claimed by the bondholders. If the asset value is higher than the notional principal of the zero-coupon bond, equity holders receive the residual value, and their pay-off increases linearly with the asset value.

The pay-off to bondholders corresponds to a portfolio composed of a risk-free zero coupon bond with notional value L, and a short put on the firm's assets, again with a strike L. If the firm is paying no dividends then by using the standard Black and Scholes (1973) call option formula, we can estimate E_t, which is the equity value of a firm by the equation (2.5):

$$E_t = A_t.\Phi(d_1) - L\ e^{-r(T-t)}\Phi(d_2)$$

$$d_1 = \frac{\ln(A_t / L) + (r + \sigma^2 / 2)(T - t)}{\sigma\sqrt{T - t}} \tag{2.5}$$

$$d_2 = d_1 - \sigma\sqrt{T - t}$$

where r is the logarithm risk-free rate of return. If we rearrange equation (2.5), we have value for A_t given by equation (2.6)

$$A_t = \left(E_t + Le^{-r(T-t)}\Phi(d_2)\right) / \Phi(d_1) \tag{2.6}$$

Then we calculate the unobservable volatility of assets σ. To calculate σ, we adopt an iterative procedure. If we go back in time, we have 253 trading days. We obtain a system of equations explained through equation (2.7):

$$A_t = \left(E_t + L_t e^{-r_t(T-t)}\Phi(d_2)\right) / \Phi(d_1)$$

$$A_{t-1} = \left(E_{t-1} + L_{t-1} e^{-r_{t-1}(T-(t-1))}\Phi(d_2)\right) / \Phi(d_1) \tag{2.7}$$

$$\ldots\ldots\ldots\ldots\ldots$$

$$A_{t-253} = \left(E_{t-253} + L_{t-253} e^{-r_{t-253}(T-(t-253))}\Phi(d_2)\right) / \Phi(d_1)$$

We compute our MPD_t using Loffler and Posch (2007)[28] computation method to implement Vassalou and Xing (2004) methodology discussed above. This process initiates by assuming asset value equals the market value of equity plus the (book) value of liabilities. Then using system of equations explained by equation 2.7, for each day we compute the asset value using the Black-Scholes formula. Using d_1, we compute d_2 and use given information to estimate equation 2.6. We then compute the log returns of the asset values, and compute standard deviation of log returns of asset values.

[28] We follow procedure explained in “Credit risk modeling using Excel and VBA” by Gunter Loffler and Peter N. Posch, Wiley Finance 2007.

This system of equations can be solved through the following iterative procedure. Iteration 0: We set starting values A_{t-a} equal to the sum of the market value of equity E_{t-a} and the book value of liabilities L_{t-a}. We set σ equal to the standard deviation of the log asset returns computed with the $A_{t-a.}$ Iteration K: We insert A_{t-a} and σ from the previous iteration into the Black Scholes (1973) formula, d_1 and d_2. We input these d1 and d2 into first equation again to compute the new A_{t-a}. Similar to iteration=0, we use A_{t-a} to compute the asset volatility. This procedure is repeated until the values of the two consecutive iterations converge. We set our tolerance level for the convergence as 10E-10. This step provides us with one unobservable variable, σ. The risk-free rate used for iteration procedure is the 1-year T-bill rate, observed at the end of the relevant month. The iteration job is to copy asset values from iteration k into iteration 0, as long as the sum of squared differences in asset values is below 10^{-10}.

For the DD formula, we also need the expected change in asset values, μ. The asset values are computed through the procedure explained in above paragraph. We now, use the standard Capital Asset Pricing Model (CAPM), to obtain the beta of the assets with respect to a market index, then apply the CAPM formula for the return on an asset i:

$$E[R_i] = R_f + \beta_i (E[R_M] - R_f) \tag{2.8}$$

where R_f is the risk-free rate, denoted by the T-bill rate observed at the end of each day. We take two different market index returns as a proxy for R_m. We use S&P 400 index values in cases where the issuer is from the S&P 400 index, and S&P 600 index values when the issuers is a constituent of the S&P 600 Index. We obtain an estimate of the asset's beta by using linear regression methods; by regressing the asset value of returns on S&P indices returns (S&P 400 and S&P600), and adding the beta value to the risk-free rate we obtain the expected asset return. This, however, is not the drift μ that we use in our formula DD formula in equation (2.4), the unknown parameter drift μ is obtained from the logarithm of these asset returns. Once we compute the DD, we use the DD formula to estimate the PD, which we denote in our study as MPD_t: We repeat the same procedure to compute MPD_t for each company in our study.

Once we estimate the MPD_t time-series for each firm, we create PD "judgmental errors" for each issuer using Moody's and S&P historical ratings data, respectively. We convert the credit ratings history of both the agencies for each firm as RPD_t (Moody's and S&P). We use S&P's annual default study table entitled "global corporate default rates by rating modifier". Using these default frequency tables for each rating category from the table, we assign a rating RPD_t to each rating in our time series. For example, a firm having a credit rating of BBB+ in 2001 is assigned a default frequency number associated with BBB+ in 2001. Secondly, if credit ratings change during year for a particular firm, we use average of the two ratings (rating before and rating after the change) to represent the rating for that particular year. Once we convert the ratings history into a rating-implied PD's represented as RPD_t for the two agencies, we estimate rating judgment error by deducting the RPD_t from the MPD_t. This is done for both the rating agencies. We term this our rating judgment error time series, and we follow same procedure for each issuer in our sample. This step provides us with a time series of issuer rating judgment errors for Moody's and S&P rating for each issuer (two time-series for each issuer). We use this time-series data for our loss function estimations in step 2.

Step 2: Loss Function Estimation

In the second step, we use the time-series of PD judgment errors to determine the shape of the rating agency's loss function. From a methodological point of view, we adapt the GMM estimation procedure for the rating agencies loss functions along the lines suggested by Elliott et al. (2005), similar relevant work on generalised preferences is undertaken by Lieli and White (2009). The method we adopt is applicable in situations where time-series data on point forecasts is available but the underlying model used by the forecaster is unknown, and is universally applicable when considering flexible loss functions (Christodoulakis and Mamatzakis, (2008) and (2009)). The outcome of this step generates loss function's alpha parameter estimates for each rating agency for each firm in our sample of firms. The advantage of using this method is, we are not required to impose any particular preference structure, as both the symmetric and asymmetric loss functions are incorporated into model. Elliott et al. (2005) also follow a flexible loss function of the form given by equation (2.9).

$$L(p,\alpha) = [\alpha + (1-2\alpha).1_{(Y_{t+1}-f_{t+1}<0)}]\left|Y_{t+1}-f_{t+1}\right|^{p} \tag{2.9}$$

In this loss function the parameter p represents the underlying assumption of the analysis. In particular, p=1 represents the double linear (lin-lin) loss function, while p=2 represents the estimations are based on a double quadratic (quad-quad) loss function. The term Y_{t+1}-f_{t+1} is the rating judgment error we define in our step 1 (MPD_t-RPD_r), while "1" is an indicator variable which takes the value of 1 if the rating judgment error $Y_{t+1}-f_{t+1}<0$ and zero otherwise. By observing the sequence of rating judgment errors (Y_{t+1}-f_{t+1}), with $\tau \leq t < T+\tau$, an estimate for α is constructed using a linear instrumental variable. The estimated α is our loss function parameter, and represents the degree in asymmetry of the loss function. α>0.5 represents rating agency's incentives to issue over-predictions, α<0.5, represents incentives to issue under-predictions, and α=0.5 yields asymmetric loss function.

$$\hat{\alpha} \equiv \frac{\left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t \left|Y_{t+1}-f_{t+1}\right|^{p-1}\right]' \hat{S}^{-1}\left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t 1_{(y_{t=1}-f_{t+1}\langle 0)}\left|Y_{t+1}-f_{t+1}\right|^{p-1}\right]}{\left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t \left|Y_{t+1}-f_{t+1}\right|^{p-1}\right] \hat{S}^{-1}\left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t \left|Y_{t+1}-f_{t+1}\right|^{p-1}\right]} \tag{2.10}$$

where v_t is a d x 1 vector of instruments, which is a subset of the information set used to generate *f*, while $\hat{S}$ is given by the equation (11). Here $\hat{S}$ depends on $\hat{\alpha}_T$ estimation and is performed iteratively, assuming S=I in the first iteration to estimate $\hat{\alpha}_{T,1}$, until convergence is achieved.

$$\hat{S} = \frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t\ v_t'(1_{(y_{t+1}-f_{t+1}<0)} - \hat{\alpha}_T)^2 |Y_{t+1}-f_{t+1}<0|^{\ 2p-2} \tag{2.11}$$

In the end, a joint test of forecast rationality and the above-mentioned loss function can be conducted with d>1 instruments utilizing a J-test statistic. Elliott et al. (2005) show that the estimator of $\hat{\alpha}_T$ is asymptotically normal, and construct a J-statistic which under the joint null hypothesis of rationality and a flexible loss function is distributed as a χ^2(d-1) variable for d>1 and takes the form given in equation (2.12).

$$J = \frac{1}{T}\left[\begin{array}{l}\left(\sum_{t=\tau}^{T+\tau-1} \nu_t \left[1_{(Y_{t+1}-f_{t+1}\langle 0\rangle)} - \hat{\alpha}_T\right] \left|Y_{t+1} - f_{t+1}\right|^{p-1}\right)' \hat{S}^{-1} \\ \times \left(\sum_{t=\tau}^{T+\tau-1} \nu_t \left[1_{(Yt+1-ft+1\langle 0\rangle)} - \hat{\alpha}_T\right] \left|Y_{t+1} - f_{t+1}\right|^{p-1}\right)\end{array}\right] \approx \chi^2_{d-1} \qquad (2.12)$$

In addition, we provide estimates for the J-statistic, under the imposed null that α takes the values 0.20, 0.50, and 0.80, these serve as additional tests in relation to the hypotheses of interest. Elliott et al. (2005) identify four instruments in their procedure (1) a constant (2) a constant and a lagged forecast error (3) a constant and lagged values of the variable to be predicted, and (4) a constant, the lagged forecast error, and lagged values of the variable to be predicted. We use first two instruments following the (Christodolakis and Mamatzakis (2008) and (2009)) method in our study. We only present results for a lin-lin function, as we have over 250 estimates of alpha parameters, and thus we are well served in determining loss function estimations.

We also conduct rationality tests using the one and two sample Kolmogorov–Smirnov (K-S) test to compare the estimated empirical distribution of the alpha parameters with the standard normal distribution. This enables us to determine uniformity in estimated alpha parameter distribution. We first conduct the one sample K-S test, where we compare rating agencies estimated parameters with a standard normal distribution. We undertake a one sample test, both with results from the whole sample and then repeat it comparing results for the two agencies from each industrial sector. This one sample test is undertaken by taking the individual alpha parameters of both the CRAs. We conduct the two sample K-S test in two ways. Initially, we test to map any differences between two CRAs parameters. This is done first by testing the differences between the results for Moody's and S&P's using the whole samples. Next we conduct the two sample test between different industrial sectors across the two CRAs. Finally, we conduct two the sample K-S test by comparing different sectors from the same agency. This tells us whether the same distribution is followed by CRAs across the different industrial sectors.

2.4 Empirical Results

In this section, we discuss our empirical results. First, we describe the descriptive statistics for our estimated PD and the estimated loss function "alpha" parameters. Then we discuss various "rationality tests" under different imposed null assumptions. We also conduct and present results for the K-S test tests relating to our loss function alpha parameter distributions. Based on our empirical results and various tests, we further discuss the economic significance of our findings and make conclusions on the preference structure of two CRAs.

2.4.1 Descriptive Statistics

Estimated PD

We begin our empirical analysis by comparing descriptive statistics for our estimated PD over our sample window from 1991 to 2009. In this study, we estimate three distinct implied PDs for a same issuer: First the MPD_t and two separate, RPD_t (Moody's and S&P). We present our results by using whole sample estimates, as well as splitting our whole sample into two subsamples for S&P 400 and S&P 600[29] index constituent issuers. In this section, the comparison of three implied PD's is carried out by estimating the yearly averages for each sample firm in a particular year. Depending upon the availability of historical credit ratings of each firm in a year, the number of firms across different years varies.

Table 2.1 presents the descriptive statistics for estimated implied probabilities of default. Panel "A" of table 2.1 presents the whole sample descriptive statistics, panel "B" uses only S&P 400 index constituent issuers in our sample and finally panel "C" compares the averages of S&P 600 index constituent issuers in our sample. If we look at the mean numbers in panel "A", we find that the highest mean values of 3.521% are for the estimated average MPD_t. The $RPD\__{Moody's}$ of 2.273% is lower than MPD_t, but higher than the $RPD\__{S\&P}$ of 1.122%. We also observe a similar trend when considering median values. These are further tested by conducting t-tests (Wicoxon Mann-Whitney tests) for the differences in the means (medians) of three different samples. We find that the differences in means and medians between the two agencies estimated RPD_t are significantly different at 1% level, with the only exception of 5% level significant difference in medians in panel C. However, we find that the difference in means

[29] S&P 600 index constituent issuers only begin from the year 1994 through 2009, as a result of data constraints

between RPD_$_{\text{Moody's}}$ and the estimated MPD_t is only significant in panel B, where we have S&P 400 index constituent firms. On the contrary, in all the three samples of differences in means and the median values of RPD_$_{\text{S\&P}}$ values are significant at 1% and 5% percent levels. This implies that Moody's on average allocates issuers to a lower rating category, resulting in having on average higher PD. However, both the agencies estimated RPD_t are lower than the average MPD_t mean and median values, with the only exception in differences in panel C sample, where the means and medians of Moody's and MPD_t are not statistically different.

In terms of other descriptive statistics, we find a higher standard deviation in MPD_t as compared to the two RPD_t. This can also be observed in a higher range between maximum and minimum values within the estimated MPD_t. Looking at the sample's skewness, we find that all three implied PD's are positively skewed. However, the value of 0.603 in RPD_$_{\text{Moody's}}$ are closer to symmetry as compared to RPD_$_{\text{S\&P}}$ value of 1.080. MPD_t has a higher degree of positive skewness suggesting lack of symmetry in average PD distribution. The kurtosis of average RPD_$_{\text{S\&P}}$ is 3.222, which is closer to the kurtosis of a normal distribution. The kurtosis of RPD_$_{\text{Moody's}}$ is 2.132 suggesting a platykurtic distributions of average yearly means. We observe a high kurtosis of 4.465 in the case of MPD_t suggesting its distribution is more prone to be impacted by outlier data.

We further segregate our PD data into two subsamples, and report the same descriptive statistics for these subsamples in panel "B" and panel "C". Panel "B" uses S&P400 index issuers and suggests the same trends as observed in panel "A". In general MP_D has higher mean and median values compared to the two RPD_t's. Similarly the mean and median values of RPD_Moody's are higher than RPD_tS&P. Looking at panel "C" where we report these statistics for S&P 600 index constituent firms, we find similar trends. This shows that the average MPD_t is higher than RPD_t's, and the mean and median values in the case of RPD_S&P are lower than RPD_Moody's. If we compare the skewness and kurtosis of our subsamples, we find that the kurtosis of both RPD_S&P and MPD_t are higher than the normal value of 3 in our panel "C" subsample. This suggests that in the case of RPD_S&P we have more outlier data values for S&P 600 index firms; the value of kurtosis in S&P 400 is very close to the normal value of 3 in panel "B" sample. Otherwise, if we compare the descriptive statistics in both panel "A" and panel "B", we find similar trends. However, the magnitude of these values is different. We observe a higher standard deviation and other statistics is panel "C" data, as S&P 600 index constituent firms are smaller firms with a correspondingly higher degree of riskiness and uncertainty attached to them. Results for Jarque-Bera test suggest the null of normality in case of MPD_t is rejected in MPD_t at 5% significance level. In RPD_S&P, the null of normality is rejected at 10% level in whole sample, whereas it is insignificant in S&P 400 index and highly significant in S&P 600 index. In RPD_Moody's we cannot reject the null of normality.

Table 2.1: Descriptive Statistics for Annual Mean PD

The table 2.1 reports the descriptive statistics for our sample of time series data of credit ratings and market implied probability default for a total of 263 firms over time period 1991 through 2009. Number of observations in each year is dependent upon the historical ratings data availability and our estimated market implied probability of default. Panel "A" reports descriptive statistics for observations of our whole sample consisting S&P 400 and S&P 600 index constituent firms. In panel "B" and "C" we report same probability of default for our segregated data by splitting whole sample into two sub samples of S&P 400 and S&P 600 index constituent firms. The four columns represent descriptive Statistics, Moody's implied probability of default, S&P implied probability of default and our estimated market implied probability of default. Last three columns show the t-Tests (Wilcoxon Mann-Whitney tests) performed to test the differences in the variable mean (medians) between the $RPD\_t_{Moody's}$-$RPD\_t_{S\&P}$, MPD_t- $RPD\_t_{S\&P}$, and MPD_t-$RPD\_t_{Moody's}$.Mean difference is the actual difference between the two means, while median (Wilcoxon Mann-Whitney tests) states the z-statistic associated with the difference.

	Moodys	S&P	Market Implied	Moodys-S&P	Moodys - Market Implied	S&P-Market Implied
Panel A: Descriptive Statistics for Whole Sample Annual Average						
Mean	2.273	1.122	3.521	1.150***	-1.248**	-2.398***
Median	2.070	0.990	2.590	2.672***	-1.343	-3.403***
Minimum	0.590	0.200	0.340			
Maximum	4.960	3.200	11.600			
Standard Deviation	1.447	0.859	2.881			
Skewness	0.603	1.080	1.341			
Kurtosis	2.132	3.222	4.465			
Jarque-Bera Test	2.540	5.31*	8.53**			
Observations*	19.000	19.000	19.000			
Panel B: Descriptive Statistics for S&P400 Index Annual Average						
Mean	1.588	0.794	3.223	0.794***	-1.635***	-2.428***
Median	1.530	0.670	2.380	2.686***	2.000**	-3.489***
Minimum	0.370	0.110	0.180			
Maximum	3.630	2.020	10.450			
Standard Deviation	1.038	0.578	2.646			
Skewness	0.653	0.913	1.139			
Kurtosis	2.214	2.776	3.962			
Jarque-Bera Test	2.580	3.960	6.700**			
Observations	19.000	19.000	19.000			
Panel C: Descriptive Statistics for S&P600 Index Annual Average						
Mean	3.678	1.831	4.134	1.846***	-0.456	-2.303***
Median	3.345	1.595	3.085	2.487**	-0.038	-2.111**
Minimum	0.940	0.350	0.640			
Maximum	8.090	6.180	13.770			
Standard Deviation	2.359	1.541	3.686			
Skewness	0.607	1.493	1.488			
Kurtosis	2.155	4.934	4.395			
Jarque-Bera Test	2.110	9.560***	8.760**			
Observations	16	16	16			

Note: Number of observations is limited to number of time-series data years. We compute annual mean for each year depend upon the number of firm's data in that particular year. For instance, in year 1995 we average all the firms estimated probability of default, and take only one mean value for 1995 to represent probability of default for the year. The final descriptive statistics is based upon annual averages in each year. The time-series data for S&P 400 index constituent firms is 19 years, and for S&P 600 it is 16 years.

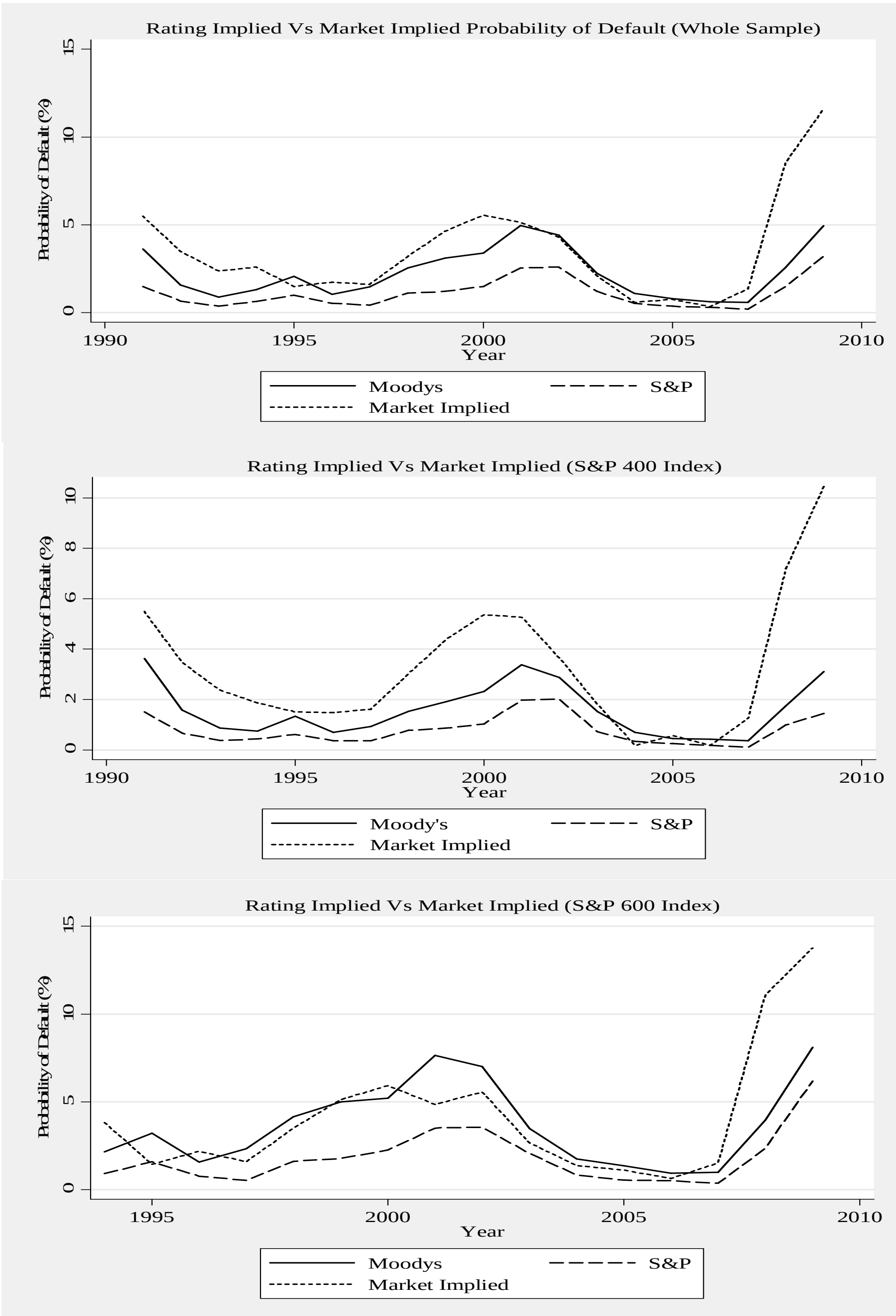
***,**,* indicate significance level at 1%, 5%, and 10% respectively

Figure 2.1 illustrates the movement of average PD numbers. Analogous to table 2.1, we illustrate the average movement of our estimated mean PD's in our sub samples as well. The first plot of figure 2.1 uses mean yearly PD's for our whole sample. From the three estimated PD's, we observe that the trends are moving in a same direction. Throughout our data window, we observe that the average MPD_t numbers are slightly higher than RPD_t's until 2003. From 2003 until 2006, all the three different sources of PD numbers are moving in the same direction and are very close to "zero" PD. However, there is a big upward jump in the MPD_t from the year 2007 onwards, and the gap between market and RPD_t's is significant in the post 2007 financial crisis period. Overall, highs and lows in PD numbers reflect the overall market conditions. During 2005-2007, we observe that PD numbers are very low. This is the time when the global financial markets had recovered from crisis in the year 2001 and we witness stable markets. During these two to three years, we can clearly see that even our MPD_t numbers are very close to zero.

Now, if we look at the second plot in figure 2.1, we observe the same trend as observed in whole sample. Our empirical results suggest that MPD_t numbers are consistently higher in our data window 1991 through 2009. In the period 2004 to 2007, we observe MP_D going below RP_D's. We observe slightly different observation in the third plot of figure 1. We find that for S&P 600 index constituent issuers, post 2001 crisis onwards, average estimated RP_D_{Moodys} numbers are higher than $RP\_D_{S\&P}$ and MPD_t. However, this higher PD number in the case of Moody's, are only observed from 2001 until 2006. In the post 2007 period, we observe in all three plots similar high gaps between MPD_t and RPD_t. This suggests that the allocation of lower ratings by Moody's, resulting in a higher PD, is more visible in S&P 600 issuer firms.

Figure 2.1 Mean Movement of Estimated PD

The figure 2.1 illustrates annual average movement of three estimated PD over our sample period spanning 19 years 1991 through 2009. The three estimated PD's are Moody's RPD_t, S&P implied RPD_t and market implied MPD_t. The first figure illustrates average PD movement of our whole sample. Second figure illustrates movement of S&P 400 index constituent firms, and the last figure illustrates S&P 600 index constituent firms average PD.



Descriptive Statistics for Estimated Alpha Parameters

In this section, we present our descriptive statistics for the estimated alpha parameters using equation (2.10) discussed in the methodology section. We present our results in two ways; first we discuss the alpha parameters' descriptive statistics for the whole sample of firms and sample (excluding financial and utility sector firms); then we present our empirical results for the alpha parameters after disaggregating the whole sample into its constituent different industry sectors.

Whole Sample Distribution and Descriptive Statistics for Alpha Parameters

To correctly interpret our results, it is important to understand what the alpha parameters estimations actually convey. In our study, we define rating judgment error as MPD_t minus the RPD_t. So, a negative rating judgment error is associated with an over-prediction of an issuers PD by the agency relative to the market, and a positive judgment error with under-predicting the PD relative to the market. The estimated loss function parameter $\alpha<0.5(\alpha>0.5)$ implies a preference structure that penalizes more heavily positive (negative) rating judgment error, i.e. under-predictions (over-predictions). In other words, $\alpha<0.5$ can be associated with optimistic preferences on the part of the rating agency relative to the markets and $\alpha>0.5$ can be associated with conservative or pessimistic preferences. Similarly, $\alpha=0.5$ reveals symmetric or neutral preferences.

Table 2.2 panels A provides the descriptive statistics for the entire sample of firms, and panel B provides the corresponding descriptive statistics for the sample excluding financial and utility sectors. The whole sample consists of 263 estimated loss function parameters. Panel "B" uses 189 observations after excluding the 74 financial and utility sector alpha parameters. The total number of firms in our sample with ratings from both the agencies is higher than 263. However, in certain cases, estimating MPD_t and loss function parameters does not generate any meaningful results[30]. In our final sample, we only include those observations where we have the complete information for all three sources of implied PD.

[30] Cases where we have very low number of time-period observations of our rating judgement error generate errors in our GMM estimation. Secondly, we also exclude firms where we are unable to generate MP_D for a particular firm.

Table 2.2 Descriptive Statistics for Estimated Alpha Parameters

The table 2.2 reports the descriptive statistics for our estimated alpha parameter under linear-linear loss. Loss function estimation results are based on our time-series of rating judgement errors defined as MPD_t (market implied PD) minus RPD_t (rating implied PD). Total number of estimated alpha parameters is based on time series data of 263 firms from S&P 400 and S&P 600 indexes. Panel "A" reports the estimated loss function parameter statistics for our whole sample of firms for both the rating agencies rating judgement errors. Panel "B" presents alpha parameters for our sample of firms excluding finance and utility sectors.

	Moody's	S&P
Panel A: Estimated alpha for whole sample		
Mean	0.559	0.464
Median	0.538	0.460
Maximum	0.999	0.999
Minimum	0.056	0.010
Std. Dev.	0.234	0.228
Skewness	0.030	0.120
Kurtosis	2.137	2.302
Observations	263	263
Panel B: Estimated alpha for sample ex finance and utility sectors		
Mean	0.618	0.502
Median	0.640	0.500
Maximum	1.000	0.999
Minimum	0.056	0.010
Std. Dev.	0.229	0.236
Skewness	-0.272	-0.152
Kurtosis	2.328	2.268
Observations	189	189

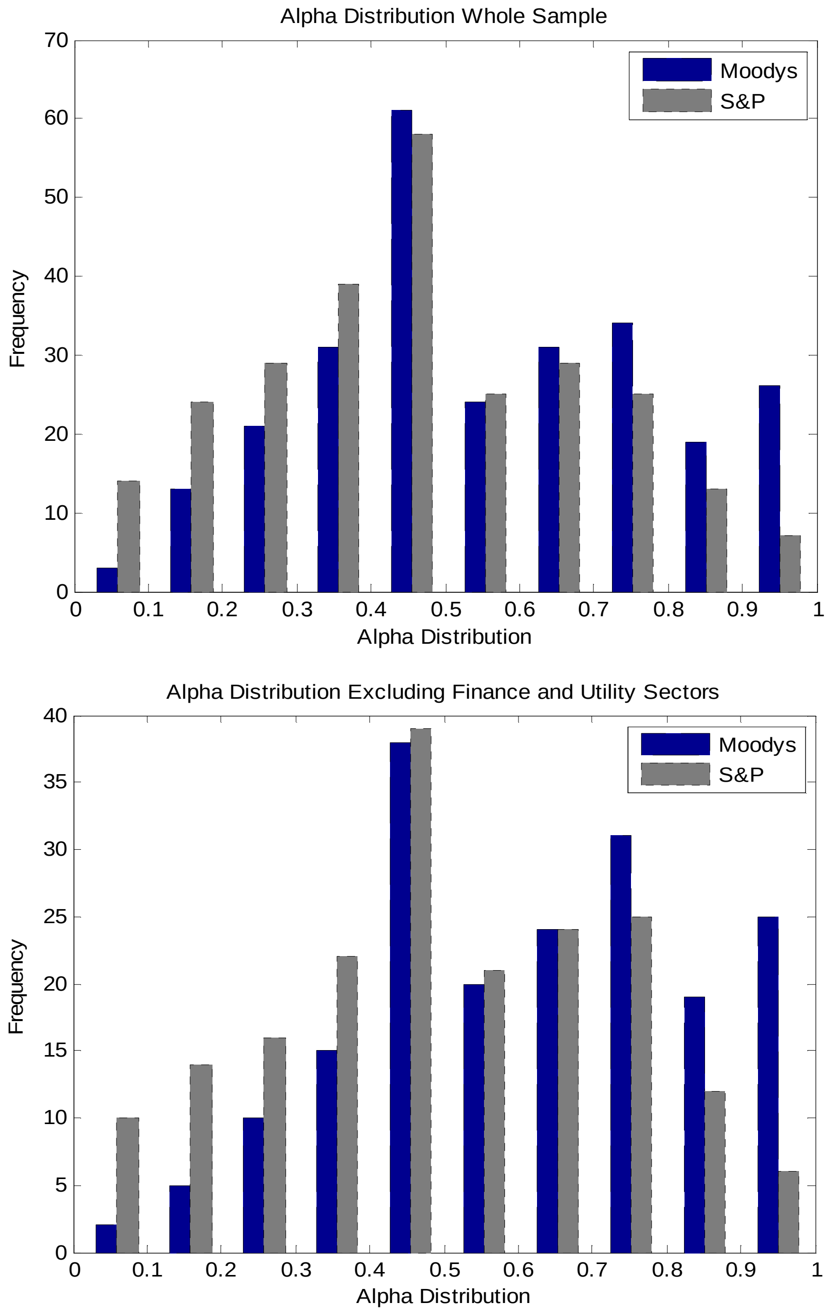
Table 2.2 panel A reveals that the mean values of the two CRAs alpha parameters are 0.56 for Moody's and 0.46 for S&P. Considering the uneven distribution of alpha parameters, it may be important to also consider median values of the two agencies alpha parameters, as we want to ensure the mean is not driven by the outliers. Moody's alphas reveal a median value of 0.54 and S&P of 0.46. Considering the degree of skewness in the two distributions, we find positive skewness in both alpha estimations for Moody's and S&P. The skewness for Moody's is 0.03 and for S&P the value is 0.12. Moody's has a kurtosis of 2.14 and S&P's a kurtosis of 2.30, which shows alpha parameters are less prone to the outliers for S&P.

Now, examining panel B of table 2.2 where we exclude financial and utility firms, we observe more pronounced differences between the preference structures of the two agencies. We find Moody's exhibits an inclination towards conservatism (or pessimism) and S&P is more symmetric. Moody's mean and alpha numbers suggest that it is more conservative, relative to the market, in assigning credit ratings. On the contrary, if we exclude financial and utility sectors from our whole sample, we observe that both the mean and median values for S&P are exactly equal to the symmetric value of 0.50. This provides strong evidence of asymmetric preferences of Moody's as compared to S&P's.

In figure 2.2, we illustrate the alpha parameter distribution. The top panel in figure 2.2 depicts our entire sample distribution and the lower panel shows the alpha parameter distribution of our sample excluding financial and utility sector firms. In the top panel, as observed in table 2.2, we find Moody's distribution higher than S&P in cases where we have $\alpha>0.50$, and S&P higher than Moody's where we have $\alpha<0.50$. However, if we look at the lower panel in figure 2.2, we find more asymmetry in case of Moody's. Moody's alpha parameters are more visibly located on the right hand side of the distribution. We find a more symmetric distribution for the S&P observations when we exclude financial and utility firms. The level of asymmetry and its significance will be further discussed, when we comment on the various rationality tests under the imposed null assumptions. We also discuss the economic significance of these preferences in terms of different incentives of rating agencies in the final section of our empirical results.

Figure 2.2 Distribution of Estimated Alpha Parameters

The figure 2.2 illustrates distribution of our estimated alpha parameter under linear-linear loss. First figure illustrates frequency distribution of alpha parameters for the whole sample and second figure shows the frequency of alpha parameter excluding finance and utility sectors



Sector Wise Distribution and Descriptive Statistics for Alpha Parameters

To further understand the degree of asymmetry in the estimated alpha parameters, we disaggregate the parameters into different industry sectors according to the definition given by GICS[31]. We perform this classification in order to observe whether the degree of asymmetry observed in the whole sample is consistent over different sectors or whether different industry sectors exhibit different behaviour. In this section, we focus only the main differences in parameter distributions and the corresponding descriptive statistics. We discuss the optimality and loss asymmetry of the two rating agencies in our next section.

Table 2.3 presents the descriptive statistics for each GICS sector is estimated alpha parameters. Panel A reports the sector descriptive statistics for Moody's and panel B reports the same descriptive statistics for S&P. In table 2.2, panel "B" where we exclude financial and utility sector, we observe asymmetry in case of Moody's and symmetry in case of S&P. If we look at the sector wise mean and median values in panel A and panel B we find consistency with our initial findings. In six sectors, namely consumer discretionary, energy, healthcare, industrial, information technology and materials, we find evidence of asymmetric preferences by Moody's and symmetric preferences by S&P. The only exception is in the case of consumer staples and telecommunications. However, both these sectors have very few observations. In consumer staples we observe symmetric preferences by Moody's with the mean value of 0.50 and more optimistic preferences by S&P with a median value of 0.330. Looking at other statistics, we find a consistency of standard deviation across different sectors in both Moody's and S&P. Moody's exhibits a negative skewness in consumer discretionary, consumer staples, energy and health care, suggesting a concentration of values on the right hand side of mean. Similarly, we observe negative skewness in consumer discretionary, energy, healthcare, industrials and information technology sectors for S&P.

For the two financial and utility sectors, we find similarities in preferences across the two agencies. In the case of financials, we find that the median value of loss function

[31]This Global Industry Classification Standard (GICS) was developed by MSCI, an independent provider of global indices and benchmark-related products and services, and S&P, an independent international financial data and investment services company. GICS sectors classify our sample firms into ten broad sectors.

alpha parameters in case of Moody's 0.40 and S&P is 0.38 both with a positive skewness, suggesting the bulk of the distribution lies on the left hand side of mean. This result is in contrast to that from other sectors, as here in the case if financial sector both the agencies show signs of optimistic preferences. Similarly, in utility sector the median value of estimated parameters in the case of Moody's is 0.421 and for S&P is 0.31. Optimistic preferences are more in evidence for S&P. The median value for Moody's differs from the other Moody's sectors, where the estimated alpha parameters exhibit an inclination towards conservatism. This shows that in both utility and financial sectors, CRAs are more optimistic. We further discuss the interpretation of these findings in our last section, where we discuss these preferences in terms of rating agencies incentives.

Table 2.3 Sector Wise Descriptive Statistics for Estimated Alpha Parameters

The table reports the descriptive statistics for our estimated alpha parameters under linear-linear loss for each sector based on GICS industry sector classification. Loss function estimation results are based on our time-series of rating judgement errors defined as RPD_t minus MPD_t. Panel “A” reports the estimated loss function parameter statistics for our sector wise estimated alpha parameters based on Moody’s rating judgement errors. Panel “B” presents sector wise alpha parameters for estimated alpha parameters based on S&P rating judgement errors.

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecommunication Services	Utilities
Panel A: Sector wise loss function alpha parameters based on Moody's rating judgement errors										
Mean	0.674	0.506	0.603	0.396	0.645	0.598	0.640	0.587	0.450	0.442
Median	0.734	0.500	0.734	0.400	0.660	0.570	0.669	0.585	0.450	0.421
Maximum	0.944	0.745	0.970	0.743	0.994	0.999	0.986	0.999	0.770	0.940
Minimum	0.056	0.251	0.075	0.102	0.124	0.125	0.330	0.210	0.130	0.164
Std. Dev.	0.205	0.154	0.276	0.162	0.251	0.216	0.190	0.260	0.453	0.195
Skewness	-0.897	-0.138	-0.633	0.161	-0.561	0.197	0.238	0.152	0.000	0.875
Kurtosis	3.353	2.351	2.070	2.497	2.573	2.341	1.942	1.820	1.000	3.315
Observations	41	10	17	52	26	47	19	27	2	22
Panel B: Sector wise loss function alpha parameters based on S&P rating judgement errors										
Mean	0.522	0.330	0.536	0.381	0.538	0.503	0.534	0.465	0.385	0.335
Median	0.530	0.355	0.570	0.380	0.585	0.500	0.550	0.460	0.385	0.314
Maximum	0.940	0.760	0.920	0.830	0.890	0.999	0.890	0.980	0.500	0.940
Minimum	0.020	0.040	0.030	0.060	0.110	0.010	0.020	0.040	0.270	0.080
Std. Dev.	0.247	0.217	0.281	0.158	0.233	0.203	0.253	0.239	0.163	0.206
Skewness	-0.298	0.457	-0.489	0.330	-0.417	-0.082	-0.508	0.422	0.000	1.226
Kurtosis	2.366	2.639	2.045	3.077	2.214	2.867	2.161	2.484	1.000	4.589
Observations	41	10	17	52	26	47	19	27	2	22

2.4.2 Evidence of Asymmetric loss

The empirical results for the estimated (true) loss function alpha parameter values and corresponding J-statistic are attached as appendix VI. The agencies results are presented separately in the same table. In each case, in the first column we show the estimated alpha while the second column shows the standard deviation. In the third column, we report the corresponding J-statistic for the estimated alpha (α) parameter which is obtained using equation (2.12) as explained in the methodology section. We repeat the procedure for the estimated alpha and corresponding J-statistic for S&P in columns seven to nine. We discuss our estimated alpha parameter results based on the data sample excluding the financial and utility sectors, followed by discussion of the estimated alpha parameters of the financial and utility sector only. We draw conclusions based on these findings, and further test their rationality based upon the imposed null hypotheses.

Appendix VI reports our estimated alpha parameters. The J-statistic reported in appendix VI is distributed as χ^2 (D-1) for our estimated true alpha $\hat{\alpha}$ explained by equation (10) and (D-1) is the degrees of freedom calculated as the number of instruments minus one. The estimation results suggest that excluding financial and utility firms, out of the total 189 issuer level estimated alpha parameters 100 (53%) of Moody's and 67(35%) of S&P, are higher than α=0.60. Similarly, 32(17%) of Moody's and 67(35%) of S&P observations are lower than α=0.40. The point estimates suggest strong evidence of asymmetric preferences in the case of Moody's estimated alpha parameters, where we find results which indicate more over-prediction of PD or a more conservative rating approach. However, the S&P loss function estimates exhibit a tendency to symmetry and we find an equal number of over and under predictions of the PD, with no evidence of a systematic over- or under-prediction of PD. Further inspection of the estimated alpha parameters in financial and utility sectors suggests strong evidence of under predictions of PD by both the agencies. We observe that out of total 74 alpha estimations in two sectors, 36(48%) of Moody's and 44(60%) of S&P observations are lower than α=0.40, whereas only 6 (8%) and 5(7%) for Moody's and

S&P respectively, are higher than α=0.60. This suggests a tendency to under-prediction from both the agencies in there sectors.

Tests of Rating Judgment Rationality

The above shape parameters provide important information about the rating agencies objectives in their allocation of loss preferences. To test the rationality of these findings, we further analyze our empirical results based on the underlying assumptions. First, we conduct our tests under the null assumption of a symmetric loss function when α=0.50. Elliott et al. (2005) suggests a test statistic of the joint null hypothesis of judgement rationality and the underlying loss function. Tests based on an assumption of Mean Squared Error (MSE) loss are closely linked to this test statistic, the difference is that if indeed α=0.50, tests based on MSE loss impose this restriction, whereas J-statistic proposed by Elliott et al. (2005) uses consistent estimate of α which is treated as unknown in our case. This justifies our selection of test, as we follow a flexible loss function. In addition, we also present our results for the J-statistic estimates, based on an imposed null hypothesis that α takes the value of α=0.20 or α=0.80. The J-statistic under various assumptions concerning the value of α, is distributed as χ^2 (D), where D degrees of freedom equal to the number of instruments used in our parameter estimations. The imposed null hypotheses serve as additional tests of the observed statistical significance of rating agencies rationality which underpins loss function preferences. In appendix VI columns four to six, we report Moody's J-statistic under the various hypotheses of interest represented by the selected α values, similarly we repeat the same exercise for S&P in columns ten to twelve. In our other two imposed null hypotheses we test the statistical significance of highly optimistic preferences (α=0.20) and highly pessimistic (conservative) preferences (α=0.80).

Table 2.4 reports the frequency of observations in which we cannot reject the null of imposed hypotheses of interest at 5% significance level. In our sample, excluding the finance and utility firms, under the imposed null of symmetry α=0.50, we observe 153 observations for Moody's and 166 observations for S&P where we cannot reject the null of symmetric preferences. Similarly in our sample only including financial and utility firms, we cannot reject the null of symmetry for 30 observations in the case of Moody's and for 37 observations in the case of S&P. However, as these may simply be due to the symmetry assumption, we next test rating judgment rationality under our other two imposed null hypothesis of interest. We first discuss our results for our sample which

Table 2.4 Frequency of J-statistic under Imposed Three Null Hypotheses

Table 2.4 reports the frequency of J statistic where we cannot reject the null hypothesis under our three imposed null hypotheses. Our three imposed hypotheses are: H_0: α=0.20, α =0.50, and α =0.80. The first and last represent the optimistic and pessimistic preferences, and the middle one represents the symmetric preferences. We present in table the frequency of our estimated J-statistic for each imposed null hypothesis where we cannot reject the null. We present our results for the whole sample for both the rating agencies and also for different GICS sectors.

	Number of Observations	Moody's			S&P		
		α=0.2	α=0.5	α=0.8	α=0.2	α=0.5	α=0.8
Whole Sample Ex Financial and Utility	189	96	153	143	124	166	114
Consumer Discretionary	41	15	30	35	22	37	28
Consumer Staples	10	5	10	6	9	8	2
Energy	17	7	13	13	7	13	11
Financials	52	42	48	21	47	46	19
Health Care	26	13	20	21	16	21	18
Industrials	47	26	39	34	31	43	28
Information Technology	19	13	16	16	14	18	14
Materials	27	16	23	16	23	24	13
Telecommunication Services	2	1	2	2	2	2	0
Utilities	22	19	19	8	20	17	4

excludes financial and utility firms. If we look at the J-statistic frequency when we impose a null of α=0.80, we find Moody’s more inclined towards conservatism. We observe that out of 189 alpha parameters for Moody’s on 143 and S&P on 114 observations we cannot reject the null of α=0.80 at 5% significance level. Whereas, in a same sample, out of 189 alpha parameters, Moody’s on 96 and S&P on 124 observations we cannot reject the null of α=0.20. This shows that the alpha parameters for S&P are equally distributed, as we observe 114 cases where we cannot reject the null of α=0.80 and 124 where we cannot reject the null of α=0.20.

Now we discuss our results based on when we segregate our alpha parameter estimations into GICS sectors. In Moody’s we find, out of total ten sectors, in seven sectors the frequency of observations for Moody’s where we cannot reject the null of α=0.80 is higher than the cases where we cannot reject the null of α=0.20. In the financial and utility sectors we find a higher frequency of cases where we cannot reject the null of α=0.20, whereas materials has an equal number of cases where we cannot reject the null of α=0.20 and α=0.80. In S&P we observe that in three sectors, consumer discretionary, energy, and healthcare, the frequency of observations in which cannot reject the null of α=0.80 is higher than the corresponding frequency when we impose the null of α=0.20. In the six other sectors, consumer staples, financials, industrials, materials, telecommunication services and utility we discover a higher frequency of cases where we cannot reject the null when α=0.20 as compared to the other imposed null of α=0.80, whereas in information technology we observe an equal number of observations where we cannot reject either the null of α=0.80 and α=0.20. In the case of S&P, when we exclude financial and utility sectors, we find three sectors in which there is a higher frequency of cases where we cannot reject the null of conservative preferences, four sectors where we find a tendency to lean towards optimism and one sector as having neutral preferences.

Above results indicate we do not find any systematic over or under prediction of PD in the preference structure of S&P. Although the results provide strong evidence that Moody's systematically over-predicts implied PD and has a more conservative preference structure. However, we also uncover fairly strong evidence of both the agencies having optimistic preferences in the financial and utility sectors, where we cannot reject the null of optimistic preferences α=0.20 in 61(82%) in the case of Moody's and 67 (90%) of observations for S&P. This is strong evidence of highly optimistic preferences by the two major rating agencies in these sectors.

2.4.3 Results of Kolmogorov-Smirnov (K-S) Test

Although each individual parameter estimate from equations 2.10 and 2.11 estimated for both the agencies is statistically significant, it is indispensable to examine whether such properties of our estimated alphas of the empirical distributions are significant or due to chance. We conduct one and two sample Kolmogorov-Smirnov (K-S) test following Christodoulakis et al. (2007) on estimated alpha parameters. We conduct K-S test to provide additional insight on the revealed differences in the empirical distributions. In one sample K-S test, we compare the values in the data vector x to a standard normal distribution. The null hypothesis is that x has a standard normal distribution. The alternative hypothesis is that x does not have that distribution. In two sample K-S test, we test to compare the distributions of the values in the two data vectors x_1 and x_2. The null hypothesis is that x_1 and x_2 are from the same continuous distribution. The alternative hypothesis is that they are from different continuous distributions. K-S test counterpart is Lilliefors test, which performs the default null hypothesis that the sample in vector x comes from a distribution in the normal family, against the alternative that it does not come from a normal distribution. Since, we not only compare our estimated alphas with the standard normal distribution, but also compare two alpha distributions with each other, K-S test serves our purpose better than Lilliefors test. We present our empirical results for K-S test in three ways. First we conduct a one sample K-S test, where the rating agency's loss function parameters are each compared with a standard normal distribution. Then we conduct two samples K-S test to observe any differences between the Moody's and S&P's empirical distributions. Finally, we conduct K-S tests across different industry sectors of the same rating agency.

One Sample K-S Test

Table 2.5 shows the results for the one sample K-S test for both the CRAs. The test statistic k presented in table 2.5 is the maximum distance between the estimated empirical and standard normal distributions. First, we look at the whole sample and subsequently we conduct a one sample test for each sector. Our empirical results reject the null of standard normal distributions in all the cases at a 1% significance level except for the telecommunications sector[32]. There is strong evidence that the estimated alpha parameter for neither rating agency is seen to follow a standard normal distribution. Figure2.3 illustrates both the empirical and standard normal distribution, and the function for shape of the function for both the rating agencies portrays this rejection of the null of standard normal distribution.

[32] In telecommunications sector we cannot reject the null of standard normal distribution. We only have two estimated alpha parameters in this sector, the results are meaningless.

Table 2.5 One Sample K-S Test

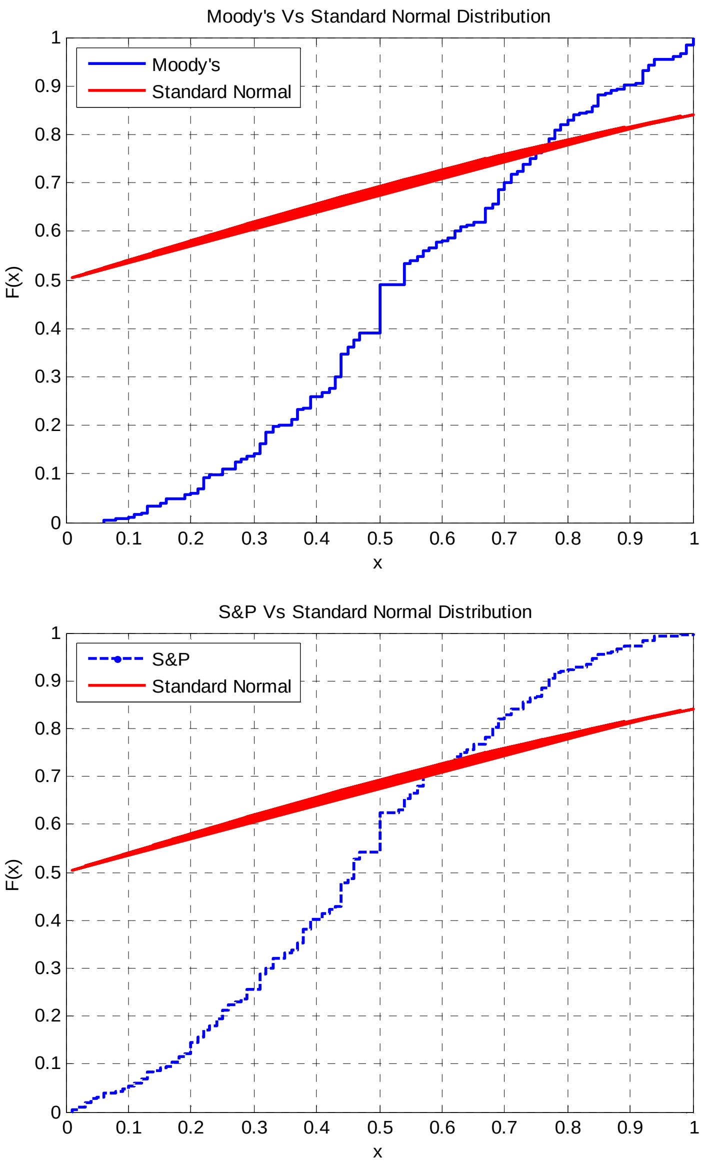
Table reports results for a one sample Kolmogorov-Smirnov test to compare the values of the estimated alpha parameters to a standard normal distribution. The null hypothesis is that estimated alpha parameters have a standard normal distribution. The alternative hypothesis is that estimated alpha parameters do not have that distribution. The test statistic "k" is the maximum difference between the curves.

	Moody's	S&P
Whole Sample	0.5327***	0.5042***
	(0.0000)	(0.0000)
Consumer Discretionary	0.6011***	0.5080***
	(0.0000)	(0.0000)
Consumer Staples	0.5991***	0.5160***
	(0.0000)	(0.0053)
Energy	0.5299***	0.512***
	(0.0000)	(0.0000)
Financials	0.5406***	0.5239***
	(0.0000)	(0.0000)
Healthcare	0.5493***	0.5438***
	(0.0000)	(0.0000)
Industrial	0.5799***	0.5289***
	(0.0000)	(0.0000)
Information Technology	0.6293***	0.5149***
	(0.0000)	(0.0000)
Materials	0.5832***	0.5344***
	(0.0000)	(0.0000)
Telecommunications	0.5517	0.6064
	(0.4019)	(0.3098)
Utilities	0.5651***	0.5319***
	(0.0000)	(0.0000)

*** represents significance level at 1%, ** significance at 5%, and * represents significance at 10%. Figures in parenthesis are the p-values

Figure 2.3 Comparison of Alpha Parameters and Standard Normal Distribution

The figure 2.3 compares the estimated alpha parameters distribution to a standard normal distribution. We perform performs a Kolmogorov-Smirnov (KS) test to compare the values of alpha parameter distribution to a standard normal distribution. The null hypothesis of standard normal distribution is rejected in both the credit rating agencies. This figure illustrates the test, first figure compares the standard normal distribution to Moody's alpha distribution, and second figure compares S&P distribution to standard normal distribution.



Two Sample K-S Test between Moody's and S&P

In this section, we perform the two sample K-S test, in order to compare the distributions of the values of Moody's and S&P's alpha parameters. The null hypothesis is Moody's and S&P are from the same continuous distribution. The alternative hypothesis is that they are from different continuous distributions. Table 2.6 presents results for our two sample K-S test. First, we conduct a two sample Kolmogorov-Smirnov test for the whole sample, and then repeat the procedure comparing different GICS sectors within our sample. In the whole sample the null of same continuous distribution is rejected at 1% significance level. This indicates that the alpha parameters from each agency do not follow the same continuous distribution. We also conduct K-S test between different industry sectors comparing the Moody's and S&P alpha parameter distributions. Our results suggest that in only one sector consumer discretionary, out of the total of ten, we can reject the null of same continuous distribution. For all the other sectors, we cannot reject the null of same continuous distribution. So, in terms of alpha distributions when we consider the entire sample of 263 observations, we find empirical distributional differences between the two agencies. However, when we study the individual sectors, these differences between the distributions are not very significant.

We present in figure 2.4 the empirical distributions of our two estimated alpha parameters for the whole sample. We also present in the same figure the empirical distribution of the consumer discretionary sector. We can observe from the plot the differences between the two agencies cdf are more visible in the case of the consumer discretionary sector.

Table 2.6 Two Sample K-S Test Moody's Vs S&P

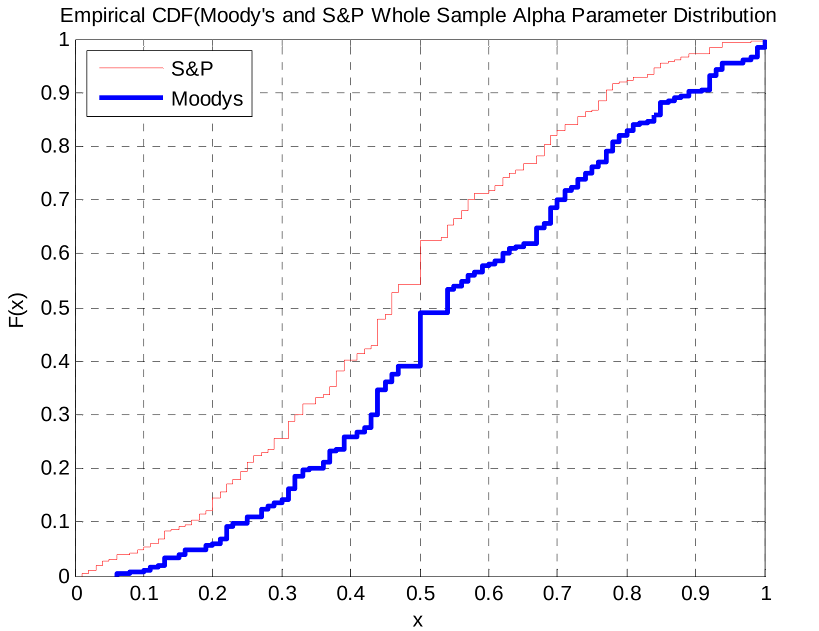
Table reports results for a two sample Kolmogorov-Smirnov (K-S) test to compare the values of the estimated alpha parameters between Moody's and S&P. The null hypothesis is that estimated alpha parameters from both S&P and Moody's are from the same continuous distribution. The alternative hypothesis is that estimated alpha parameters are from a different continuous distribution. The presented test statistic "k" is the maximum difference between the curves.

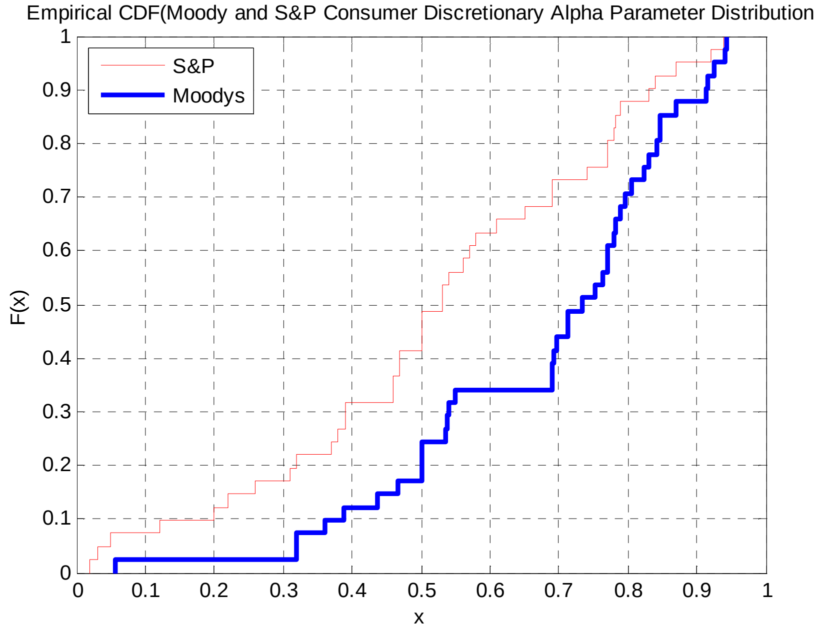
Whole Sample	0.1521***
	(0.0040)
Consumer Discretionary	0.3659***
	(0.0048)
Consumer Staples	0.5000
	(0.1108)
Energy	0.2353
	(0.6725)
Financials	0.1154
	(0.858)
Healthcare	0.2308
	(0.4402)
Industrial	0.1915
	(0.3207)
Information Technology	0.2105
	(0.7415)
Materials	0.2593
	(0.2793)
Telecommunications	0.5000
	(0.8438)
Utilities	0.3182
	(0.1746)

Note: *** represents significance level at 1% (0.01), ** significance at 5% (0.05), and * represents significance at 10% (0.10).

Figure 2.4 Comparison of Empirical Distribution (Moody's Vs S&P)

The figure 2.4 compares the estimated alpha parameters distribution of two empirical distributions. We perform a Kolmogorov-Smirnov (KS) test to compare the values of alpha parameter follows same distribution. This figure illustrates the test, first figure compares the standard normal distribution to Moody's alpha distribution, and second figure compares S&P distribution to standard normal distribution.





Two Sample K-S Test between Moody's (S&P) Sectors Vs Moody's(S&P Sectors)

We also conduct a two sample K-S test between estimated alphas for different industrial sectors within same rating agency. These results test whether the same continuous empirical distribution is followed across different pairs of sectors with same agency. The final KS-test matrix is given in table 2.7, which summarizes our test results. For both our rating agencies, we find that in a majority of cases when we reject the null of same continuous distribution, either financial or utility sector firms are involved. In Moody's sector versus Moody's sector matrix, we find that out of a total of 17 observations where we reject the null of same continuous distribution, 11 observations where one sector involves the financial or utility sector. Similarly, in the case of S&P we find that out of 16 observations where we reject the null of the same continuous distribution, 11 observations are from a comparison involving either the utility or financial sector. S&P is an exception in rams of the consumer staples sector where we reject the null of same continuous distribution with energy, health care, industrial, information technology. In Moody's we find similar observations for the consumer discretionary sector.

This implies that within agencies, a majority of cases where we reject the null of the same continuous distributions involve either the financial or utility sectors. We find some evidence of different continuous distribution in the consumer discretionary sector and for S&P in the consumer staples sectors. However, more pronounced differences are observed in the financial and utility sectors. In earlier sections, we provide evidence that both agencies have more optimistic preferences in the financial sector. These K-S tests further provide statistical significance of our earlier findings. We discuss the economic significance and previous literature findings on these preferences in our next section.

Table 2.7 Two Sample K-S Test Moody's (S&P) Sectors Vs Moody's (S&P) Sectors

Table 2.7 reports results for a two sample Kolmogorov-Smirnov test to compare the values of the estimated alpha parameters between Moody's(S&P) sectors versus Moody's (S&P) sectors. The null hypothesis is that estimated alpha parameters from different Moody's (S&P) sectors are from the same continuous distribution. The alternative hypothesis is that estimated alpha parameters from different Moody's (S&P) sectors are from a different continuous distribution. The test statistic k is the maximum difference between the curves.

S&P Sectors Vs S&P Sectors

Moody's Sectors Vs Moody's Sectors

Sectors	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom Services	Utilities
Consumer Discretionary	0	0.4878**	0.2138	0.6008***	0.2739	0.3181**	0.2452	0.3252**	0.4756	0.5676***
	-1	(0.0281)	(0.5878)	(0.0000)	(0.1534)	(0.0180)	(0.3652)	(0.0495)	(0.6242)	(0.0000)
Consumer Staples	0.4829**	0	0.4882*	0.4308*	0.4538*	0.3106	0.3263	0.3185	0.5	0.3818
	(0.0305)	-1	(0.0663)	(0.0628)	0.0707	0.3384	0.4089	0.3769	0.6304	0.2085
Energy	0.1736	0.4882*	0	0.5701***	0.2036	0.2904	0.2415	0.3137	0.4412	0.4973**
	(0.8250)	(0.0663)	-1	(0.0000)	(0.7373)	(0.2025)	(0.6084)	(0.2097)	(0.7452)	(0.0107)
Financials	0.3841***	0.2615	0.4729***	0	0.5962***	0.4186***	0.5202***	0.3974***	0.50000	0.1206
	(0.0015)	(0.5462)	(0.0040)	-1	(0.0000)	(0.0000)	(0.0000)	(0.0049)	(0.5547)	(0.9687)
Health Care	0.1341	0.4923**	0.1810	0.4231***	0	0.2283	0.2045	0.2123	0.4231	0.528***
	(0.9178)	(0.0392)	(0.8532)	(0.0026)	-1	(0.3063)	(0.6967)	(0.5371)	(0.7740)	(0.0014)
Industrials	0.1832	0.4234*	0.2841	0.3335***	0.1809	0	0.1713	0.1529	0.4787	0.3627**
	(0.4159)	(0.0744)	(0.2232)	(0.0060)	(0.5995)	-1	(0.7828)	(0.7835)	(0.6128)	(0.0285)
Information Technology	0.1322	0.4842*	0.1486	0.4443***	0.1377	0.187	0	0.2437	0.4787	0.3627**
	(0.9662)	(0.0619)	(0.9807)	(0.0052)	(0.9767)	(0.6846)	-1	(0.4638)	(0.6128)	(0.0285)
Materials	0.1879	0.3185	0.2919	0.2507	0.2422	0.1946	0.2456	0	0.5	0.3485*
	(0.5674)	(0.3769)	(0.2832)	(0.1828)	(0.3687)	(0.4891)	(0.4536)	-1	(0.5727)	(0.0810)
Telecommunication	0.5122	0.4	0.5882	0.2885	0.5385	0.4681	0.4681	0.5	0	0.5
	(0.5287)	(0.8663)	(0.3847)	(0.9848)	(0.4777)	(0.6412)	(0.6412)	(0.5727)	-1	(0.5809)
Utilities	0.5011***	0.2273	0.4973**	0.2622	0.542***	0.4961***	0.4961***	0.3485*	0.4545	0
	(0.0000)	(0.8182)	(0.0107)	(0.2025)	(0.0000)	(0.0000)	(0.0000)	(0.0810)	(0.6997)	-1

Note: *** represents significance level at 1% (0.01), ** significance at 5% (0.05), and * represents significance at 10% (0.10).

2.4.4 Economic Significance and Incentives

Our empirical findings and further statistical test results suggest an asymmetric shape for Moody's loss function, where we find evidence leaning towards conservative preferences. In the case of S&P, with the exception of financial and utility sectors, we observe evidence of symmetric loss function. Both the mean and median value of our sample, excluding financial and utility firms, suggest a more symmetric preference structure is exhibited by S&P, and we do not find strong evidence of the systematic under- or over-prediction of PD for this agency. These results suggest S&P reflects market sentiments more than Moody's. Together, these two agencies cover credit assessment for all industry sectors, and are mostly referred to those agencies used under regulatory requirements as well as by investors. They are both paid by the issuer firms for a rating, and have access to firm level confidential information. This suggests that the users of these agencies consider the rating information they provide to have economic significance, as their investment decisions are influenced by the final credit assessment of these two organizations. However, critics of rating agencies suggest that due to the issuer pay model (used by both the agencies) the two agencies may have incentives to under estimate PD, as this may help its clients significantly reduce their cost of capital and be eligible for consideration in more investment opportunities. Our results for the majority of sectors, other than financial and utility, suggest otherwise. Indeed, if anything we observe evidence that CRAs act against these general incentives to under estimate PD.

Beaver et al. (2006) suggest that NRSRO firms are mostly used for regulatory and contractual purposes, and these requirements required more conservative approach towards credit assessment. We complement Beaver et al.'s (2006) findings in that Moody's appears to be more conservative in sectors other than financial and utility. However, S&P, an equally important NRSRO firm, exhibits more symmetric preferences. This suggests that the conservative approach associated with NRSRO firms is not applicable across all NRSRO CRAs, as it only characterizes Moody's loss function preferences. In terms of costs, as suggested by the findings of Jewell and Livingstone (1998) and Hseuh and Kidwell (1998), market participants take split rated bonds as a separate credit quality, with market yields on these bonds equivalent to an average of the higher and lower ratings in a split. These results suggest that issuers of these bonds bear higher costs, in cases where Moody's is over-predicting their PD.

Beaver et al. (2006) suggests certified agencies (NRSRO) ratings are also used in a variety of contractual settings; hence these agencies also play a role of a quasi-regulatory role as the SEC regulations effectively require all bond issues to be rated by at least one certified agency. The conservative loss function preferences by Moody's suggest the agency has more incentives to be acting as a quasi regulatory body. Cheng and Neamtiu (2009) and Covitz and Harrison (2003) suggest that reputation incentives are important to rating agencies, and consistent with this incentive we find Moody's results also suggest reputation incentives are more important to CRAs. A desire to obtain preferential treatment in regulatory and contractual arrangement may force issuers to seek Moody's ratings. A Second reason could be that Moody's uses a more stringent methodology to rate corporate issuers as compared to S&P.

In addition, Beaver et al. (2006) link a symmetric loss function preference structure of rating agencies to the use of their ratings by investors, as agencies need timely action on both good and bad news. They conclude that EGR a non-certified agency has incentives to have symmetric preferences, as it is widely used for investment purposes. However, the three major credit rating agencies; Moody's, S&P, and Fitch each offer ancillary consulting services [33] to different clients. These services include rating assessment services, whereby they provide an evaluation of the impact of a contemplated corporate action on an issuer's rating. These services are mainly used by investment houses for portfolio compliance. Other services include risk management and consulting services which are designed to assist financial institutions and other corporations in their management of credit and operational risk (Rousseau (2006)). S&P [34] symmetric preference structure suggests it equally punishes good and bad news, and these incentives to be timelier may derive from these ancillary services provided to investment related clients.

Our results for the financial sector provide interesting reading. We find rating agencies under-predict estimated PD within this sector, and we also find significant statistical differences in the distribution of the agencies alpha parameters as compared to other

[33] IOSCO Report, supra note 4 at 4; Report on the Role and Function of CRAs, supra note 4 at 42.

[34] See McGraw-Hill Companies Form 10-K Filing, 2001: "S&P's revenue from rating evaluation services . . . increased substantially during 2000."

sectors. These results suggest rating agencies adopt a 'laxer' methodology towards this sector, resulting in an under-prediction of implied PD as compared to that provided by market-based methods. Morgan (2002) states the asset opacity associated with financial institution may be a major reason behind credit rating agency disagreement. He finds split credit ratings between two agencies are more visible and plausible for banks, which he attributes to an asset opaqueness issue. Golin (2001) and Poon and Firth (2005) state the conservatism in unsolicited ratings is due to limited information which brings a more cautious attitude in such cases. These findings suggest that asset opacity associated with financial institutions may generate a more limited information set, resulting in more cautious standards being adopted by the rating agencies. However, we find more lax standards arise in the case of financial institutions, reflected in an under-estimation of PD relative to the market estimates. This finding is in contrast to other sectors. One possible reason behind this phenomenon is that financial institutions work in a highly regulated sector, leading rating agencies to adopt a more lenient approach towards this sector is consistent with "too big to fail regulatory approach". However, the asset opacity and private information literature suggests rating agencies would have more stringent standards for these financial sector firms. Our results suggest otherwise, and they are in line with this asymmetry linked to conflict of interest arising due to "issuer pay" model.

We also find similar optimistic loss functions within the utility sectors of both the agencies. The U.S. utility sector underwent deregulation through Public Utility Regulatory Policies Act (PURPA) in 1978 and Energy Policy Act (EPAct) in 1992. This deregulation enhances the competition and reduces government role in the utility sector. Before the deregulation, utilities enjoyed rate protection and monopoly status. The introduction of deregulation may enhance both the competition and uncertainty associated with future earnings. This deregulation may force CRAs to lower their ratings on utility sector firms after the introduction of deregulations, as uncertainty associated with future may lower credit quality of a utility firm. Cheng and Neamtiu (2009) study the response of CRAs over failure to predict high profile bankruptcies like Enron and California Utilities and increased regulatory pressure, and conclude that rating agencies have improved timeliness and rating accuracy in the post-regulatory period. Their study is not specific to utility sectors, but includes other sectors as well. However, both the high profile cases discussed relate to utility sector. Maung and

Mehrotra (2010) study the utility sector and find that the credit quality decline suggested by the Blume et al. (1998) study is less pronounced in the utility sector. This asymmetry evidenced in the utility sector suggests that rating agencies are still lax over utility firms, and it maybe this which is driving our loss function to be asymmetric.

2.5 Concluding Remarks

This chapter provides estimates of loss function parameters across both Moody's and S&P. To the best of our knowledge, this is the first study that applies loss function estimation method in a credit ratings context. We estimate loss function parameters following the Elliott et al. (2005) methodology, as this method is applicable in situations where we have time-series data but the underlying model is unknown. Using a sample of nineteen years starting 1991 through 2009, we define our rating judgment error as the difference between the MPD_t and the RPD_t. We use the Merton (1974) model to estimate MPD_t following the Vassalou and Xing (2004) methodology. Our empirical results suggest CRAs loss function preferences, rationality and incentives appear to vary across the two major rating agencies.

Our results suggest a systematic asymmetry of loss function preferences in Moody's, whereas we find evidence of symmetric loss function estimates for S&P. However, across both the agencies, we find a similar asymmetry in the utility and financial sectors. In Moody's, apart from the financial and utility sectors, we find strong evidence of conservative preferences. This finding is further tested through imposing various rationality assumptions, and a similar asymmetry is observed across various industry sectors. In S&P, we do not observe any consistency in loss function alpha parameters. We observe pessimistic as well as optimistic preferences, although the median value of the sample excluding financial and utility sectors suggest symmetric preferences. Across both the agencies, we find financial and utility sectors to have more optimistic preferences. Our results suggest, as a result of the under-prediction of RPD_t, that the bulk of estimated alphas are lower than one half resulting in optimistic preferences.

Beaver et al. (2006) documents regulatory and contractual needs force NRSRO firms to be more conservative. We find Moody's more conservative across sectors other than financial and utility. We further add to Beaver et al. (2006) findings in three directions: First we estimate loss function preferences for the first time, second, we provide evidence Moody's is not conservative across every sector, as Moody's follows optimistic preferences in financial and utility sectors, Finally, we provide evidence that the conservative preferences associated with Moody's cannot be generalized across all NRSRO firms, as we document more symmetric preferences from S&P. We conclude S&P credit ratings reflect market sentiments and Moody's conservative approach is in line with the regulatory uses of credit ratings.

In both the agencies, asset opacity associated with financial institutions may result in limited available information, perhaps resulting in more cautious standards by the rating agencies. However, in contrast we find more lax rating standards occur for financial institutions, resulting in under-estimation of PD, a finding consistent across both agencies. We also find similar optimistic asymmetric loss function within the utility sector ratings of both agencies. The utility sector underwent deregulations in 1978 and 1992; these series of deregulations remove price protection and monopoly status from utility sector firms. These deregulations suggest a downward push on credit ratings, as increase in competition is associated with more uncertainty about future earnings of a firm. Cheng and Neamtiu (2009) find rating agencies have improved timeliness and rating accuracy in the post-regulatory period. However, our findings imply rating agencies still have lax standards towards this industry even after deregulations. Even after occurrence of high profile cases such as Enron and California Utilities the utility sector firms still enjoy higher credit ratings resulting in under-prediction of PD compared to market.

Our results are based upon a comparison on MPD_t following the Merton (1974) model; indeed, we do not argue over the best predictor of MPD_t. Our results provide some comparisons between the rating judgment of the two agencies, and further work can be done to obtain a better proxy to capture market sentiments. Second, we document some limitations in terms of implied rating based PD, as our results are based upon ex-post default rates. CRAs do not publish the implied (ex ante) PD associated with their ratings, we use a single agency default rate for both our comparison and loss function estimations.

Chapter 3

The Determinant of Corporate Credit Rating: New Evidence from S&P and Moody's.

Summary

The study compares the impact of financial, governance and other variables in determining issuer credit ratings between two major CRAs, S&P and Moody's. This is the first study that investigates the predictive power of factors other than financials in determining credit ratings. Utilising a sample of 5192 observations from S&P400, S&P500 and S&P600 index constituent issuer firms, we employ an ordered probit model on a panel data set spanning 1995 through 2009. The empirical results suggest that the agencies indeed differ on the level of importance they attach to each variable. Results reveal that our data explains Moody's ratings slightly better than S&P. We conclude that financial information remains the significant factor in the attribution of credit ratings for both the agencies. We also examine the relationship between governance variables and ratings, but find no significant improvement in the predictive power of credit rating using governance related variables. Our other factors show strong evidence of continuing stringent standards, reputation concerns and difference of standards during economic crises by the two rating agencies. In addition, by adding our selected proxies for potential criticism of credit rating agencies in our model specification, we find a significant improvement in allocation of a high credit rating category. This suggests more subjective elements at work in allocation of higher credit ratings by the two agencies.

3.1 Introduction

Moody's and S&P dominate the global credit rating industry[35]. Both these agencies employ an analyst-driven approach, where they express an opinion on the relative future creditworthiness of both individual issuers and debt issues. These analysts base their opinion on both the utilisation of qualitative and quantitative information, utilising information such as historical financial performance indicators, policies, and risk management strategies of particular issuer to assess the business and economic environment in which the issuer operates. These analysts have access to information that other market participants lack. Despite stating their rating process and methodology, the information that underpins credit ratings still remains a fundamental research question. This is due to the subjective element involved in determining both the ratings process and individual rating agency preferences.

The two major agencies rate every new bond issue in the U.S. market on the basis of an unsolicited rating, and also charge issuers[36] in the case of solicited rating. The two agencies appear to have a reasonably similar credit rating process[37]. This published process is for credit rating assignments to first time issuers, when a rating agency signs a contract that allows them to have access to issuer management and other classified information. At the end of the first-time rating process, issuers can ask for a review by providing additional information, as well as agree to a delay in the public announcement of the rating or request to or keep the rating confidential. However, both the agencies maintain that they do not permit issuers to disclose their rating on a selective basis.

The first time issuer rating process begins with a meeting of agency analysts and the issuer's management, where the management is informed regarding the rating's process and is asked for additional information. Generally these meetings with the issuer management seek information regarding industry trends, management quality,

[35] Moody's rating business started in the year 1909, while two companies that combined to become S&P originated in the years 1916 and 1922.

[36] The major change for the rating industry came in the early 1970s, when the industry changed its business model from the "investors pay" model to an "issuers pay" model.

[37] The rating process can be accessed through following links for Moody's use http://www.moodys.com/ratings-process/How-to-Get-Rated/002001 and for S&P use http://www.standardandpoors.com/aboutcreditratings/

competitive position, management strategy and attitude towards risk-taking, financial position and sources of liquidity. Subsequent to the initial meeting, analysts at the agencies continue the credit analysis based on any published financial information and other information gathered through site visits. They generally follow-up on the initial discussions and seek clarifications over disputed or fuzzy information. Upon completion of the initial assessment and industry analysis, analysts make recommendation to the rating committee of the particular rating agency. Based on the recommendations from this assessment, and input from all the other relevant experts in different areas, the rating agency prepares an issuer credit rating. According to Moody's this process of initial rating takes approximately sixty to ninety days.

Once a rating is finalized by a ratings committee, the rating is discussed with the management of an issuer. If the rating is approved by the issuer management, this rating would be publicised through a press release to the financial media worldwide. Once a rating is announced, the two CRA analysts maintain an ongoing relationship with the management and undertake continued surveillance of issuer activities and performance.

The main purpose of the credit analysis is to focus on an issuer's long-term risk profile. The published rating signifies an agency's perceived view on the future risk profile of an issuer and its relative position within particular industrial sector. Moody's[38] states that their ratings are not intended to ratchet up and down with business or supply-demand cycles or to reflect short-term market movements. S&P[39] maintains that their ratings are forward-looking and in assigning ratings, they anticipate the ups and down of business cycles, as well as trends and events that can be reasonably anticipated. Both the agencies maintain that the ratings are not static and can alter if any significant event occurs that raises question concerning the credit quality of an issue or an issuer that was not expected at the time rating was assigned. The importance and use of credit rating information is widespread. However, criticism of CRAs is also not a new phenomenon. The abrupt downgrading of East

[38] Moody's rating methodology available on www.moodys.com

[39] S&P document "What credit ratings are & are not" available on the website http://www.standardandpoors.com

Asian countries, subsequent to the onset of the Asian crisis and also of prominent companies like Enron and WorldCom which occurred only after serious problems manifest themselves raise questions with respect to the forward-looking approach of CRAs.

The 2007-08 global crisis only served to exacerbate the criticism and instigated several actions by the relevant authorities. In August 2007, the SEC Staff initiated examinations of three CRAs, Fitch, Moody', and S&P rating services, to review their role during the 2007-2008 financial turmoil. The report uncovered significant weaknesses in ratings practices and recommended a need for remedial action by the agencies to provide meaningful ratings and the necessary levels of disclosure to investors. Recent actions by the US [40] and European [41] authorities are a clear indication of the concerns and seriousness of this issue and its potential damage to the whole system.

This study proposes a new set of variables in order to investigate determinants of the credit ratings assigned by Moody's and S&P. It also compares the significance of these determinants across the two CRAs. We aim to develop a relationship between the variables already shown to have explanatory power in the current literature, and also incorporate additional variables that capture more subjective elements of the decision making process in rating assignment. We explore whether our set of variables predict one agency's decisions better than the other. Explicitly, the study investigates the following research questions: Does the analysis of financial variables reveal a fundamental difference between the standards and importance of these factors in the allocation of ratings between Moody's and S&P? Do governance variables enhance the prediction capability of our model? Do issuers who engage in rating shopping obtain different ratings than institutions with only two ratings? Is any difference in standards revealed between the two agencies after the introduction of favourable regulations from SEC? Are the firm ratings impacted by economic

[40] In 2010, US Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act. The law imposes several changes to disclosure practices of CRAs and calls for a separate regulatory board to monitor CRAs.

[41] In April 2009 the European Parliament approved legislation to regulate CRAs in the European Union. These legislations are directed towards both the individual analysts and overall business structure of the CRAs.

crises? Finally, do the agencies follow different standards across different stages of the business cycle?

The study uses financial variables that are considered to be important by the rating agencies in their stated policies. We also include three governance variables found to have explanatory power in determining credit ratings by previous studies, and three additional variables what we believe set as proxies to address general criticism and subjectivity in the rating process. We focus exclusively on two major agencies i.e. S&P and Moody's, utilising a sample of 5192 observations from S&P 500, S&P 400 and S&P 600 index constituent issuer firms. We use the maximum likelihood methods proposed by Blume et al. (1998) using an ordered probit model to analyse dataset spanning1995 through 2009.

Our results suggest that the agencies indeed differ on the basis of the level of importance they attach to certain variables when allocating credit ratings. Empirical results suggest our data explains Moody's credit ratings slightly better than the S&P's. Financial information relating to an issuer such as coverage, leverage, profitability and market beta remains a significant factor in determining issuer credit ratings. The study finds no significant improvement in prediction rates subsequent to adding three governance related variables. However, our selected proxies designed to highlight general criticisms and subjectivity of rating assignment processes significantly improve rating prediction. This improvement in prediction accuracy is significant in case of more highly-rated issuers that were the least able to be predicted in the previous literature. We find strong evidence of continuing stringent standards, as adding a proxy for favourable regulation from SEC has helped rating agencies to have more stringent rating process through our data window. Another criticism on the rating agencies is that they help issuers with their rating shopping behaviour in order to achieve desirable higher credit ratings. We find that the two major rating agencies have more stringent standards for issuers with more than three credit ratings, suggesting reputational concerns overweigh general criticism. We also find strong evidence that the CRAs follow different standards across different business cycle periods. In particular, we find evidence of more conservative approach during crises periods. This finding is against the stated policy of the two rating agencies, where they maintain that they consider ups and downs of business cycle when they asses a particular issuer.

The study extends current literature in various directions. To our knowledge this is the first study to compare and combine financial, governance and other factors when analysing the determination of credit ratings. Governance has previously been associated with credit ratings[42] in terms of its significance in explaining credit ratings, however to our knowledge in terms of improvement in predictive power by adding governance related variables in not covered in the current literature. This study does not limit itself to adding governance factors to supplement control issuer financials; we use a set of new variables as proxies to examine the relationship between credit ratings an attempt to capture the general criticism and subjectivity involved in the rating process. We find that we are able to improve our ability to predict credit ratings on the basis of our new set of variables. Previous studies[43] fail to predict high rating category firms, with possible reasons given being the subjective element involved in discriminating between the top rating categories. This study extends previous literature by providing considerable improvement in the prediction success rate for high rating categories.

The organization of the remainder of this chapter 3 is as follows: Section 3.2 provides a literature review, Section 3.3 describes the sources and definitions of the data utilised, and also presents the ordered probit model used in estimations. Section 3.4 describes the empirical results and discusses the findings and the robustness of results. Finally section 3.5 concludes the study.

3.2 Literature Review

There is a large literature examining the attribution of different factors to the determination of credit ratings. The literature revolves around three major branches. The first branch addresses the question of whether credit ratings in fact measure what they are supposed to measure (see Ang and Patel (1975) and Kau and Wu (1990)). The second branch asks whether credit ratings convey any additional

[42] See for instance, Bhojraj and Sengupta (2003) and Ashbaugh et al. (2006)

[43] See for instance, Horrigan (1966), West (1970), Pogue and Soldofsky (1969), Pinches and Mingo (1973 and 1975), Altman and Katz (1976), and Kaplan and Urwitz (1979), Blume et al. (1998)

information that the market has not yet incorporated into bond and equity prices from other available information (see for instance, Katz (1974), Grier and Katz (1976), Weintein (1977), Wakeman (1978), Ingram et al. (1983), Hand et al. (1992)). The third and final branch, which is closest to our study, analyses whether available public information can be used to predict credit ratings. This third branch of literature is thoroughly covered in this study. This chapter utilises this branch of literature in informing our selection of a range of explanatory variables. However, we also extend this literature, as we do not limit the present study to the inclusion of only accounting and financial-based variables.

The literature review below is organized into three main sections. The first section covers previous studies analysing how financial information is used in attribution analysis. The second section covers, other than accounting and financial information, those previous studies that use additional factors which have been shown to possess explanatory power. The third section addresses previous studies that have explored potential conflict of interest issues and subjectivity in the credit rating process.

3.2.1 Financial Information and Estimation Methods

The first study to use financial ratios to determine long-term credit ratings is Horrigan (1966). He uses simple linear regression to associate financial ratios with long-term credit ratings. The sample Horrigan uses consists of firms whose bond ratings do not change during his six year period that starts in 1959 and ends in 1964. His sample includes 201 firms with stable Moody's ratings and 151 firms with stable S&P ratings. He carries out his study in three stages by converting credit ratings into numerical numbers. In the first stage, he selects only those independent variables which are correlated with the credit ratings. Based on the measured correlations between the independent variables with the dependent variable, the study discards uncorrelated variables. In the second stage, he carries out linear multiple regressions by converting credit rating into numerical numbers and using it as the dependent variable. Lastly, he tests his results on out-of-sample data. The financial ratios used in the study to associate with credit ratings are: working capital to sales; net worth to total debt; sales to net worth; and net operating profit to sales. He also uses total assets as an explanatory variable. The study concludes that financial ratios, total assets and a dummy for subordination status are able to predict half the bond ratings out-of-sample. He concludes that financial ratios and accounting data can be useful in long-term credit administration. Horrigan’s method has certain shortfalls when used in credit rating scenario. Credit ratings are discrete in nature, and take on a finite number of values possessing a natural ordering.

West (1970) uses linear regression method to predict credit ratings. He provides an alternative method to that used by Horrigan (1966). He uses the Fisher (1959) approach as an alternative to the Horrigan approach, using linear regression analysis and the logarithms of credit ratings as dependent variable regressed on the logarithm of the independent variables. The Financial and Accounting ratios used in the study are: earnings variability, period of solvency, the equity to debt ratio and bonds outstanding. As an alternative to the Horrigan approach, he uses five-cross sections over five different years. His argument is that the initial study concludes on the basis of only one year of financial ratios. West (1970) uses five years of data by keeping a five year gap between each of the different cross-sections starting with bonds in 1927 going to the last year of his sample in 1953. His main contribution lies in the use of multiple years instead of relying on one year financial ratios. In terms of importance of financial ratios and accounting information, his results are not very different from Horrigan (1966).

Another study using linear regression is Pogue and Soldofsky (1969). They conduct their study by assigning numerical values (1,0) to credit rating categories, and observe relative probability of having higher or lower rating within four different pairs, i.e. by using first dependent variable (1,0) as probability of Aaa rather than Baa rating. The explanatory variables used are: total assets, total debt to capital, net profit to total assets, variation of net profit to total assets, and (net profit plus interest) to interest charge. The probability they measure is the function of measures of leverage, profitability and firm size. Using Moody’s bond ratings they also classify data into three industrial sectors, using industrial dummies to show inter-sector differences. Their results suggest that bond ratings are inversely related to the leverage and earnings instability, and positively related to firm size and profitability. They find that leverage and profitability have the greatest impact on the bond ratings.

The accuracy of their model in predicting ratings improves when the difference between the categories compared is greater (Aaa Vs. Baa as opposed to Aaa vs. Aa). They avoid the problems associated with using ordinal numbers as in Horrigan (1966); however, they fail to incorporate full rating information simultaneously, as they only consider two rating categories at a time. Moreover, as the rating categories are in order, their model is unable to predict two consecutive rating categories, but is more efficient when the difference in rating categories is higher.

After the initial linear regression model approaches, an alternative econometric technique to associate credit ratings with the available financial information is developed by Pinches and Mingo (1973). They use their technique on a data sample of 180 firms, with 132 firms forming the original sample, and the rest forming a holdout sample. They adopt a two-stage approach to associate bond ratings with financial and accounting variables. In the first stage, they use factor analysis to select a range of explanatory variables. For this purpose they collect financial data on thirty-five different variables, and financial data is screened by factor analysing the data. Following an analysis of the independent dimensions in the data, six major factors are used for further analysis: subordination, years of consecutive dividends, issue size and three financial ratios. In the second stage they use a multiple discriminant approach (MDA) to classify bonds into rating categories by constructing linear functions that distinguish between categories by maximising the ratio of between-category variance to within-group variance. A subsequent study by Pinches and Mingo (1975) attempts to eliminate the subordinated variable and compensates by using a more sophisticated classification rule.

Altman and Katz (1976) apply MDA to the bond ratings of companies in the electric public utility industry. Starting from an initial list of 30 variables, a series of ad hoc procedures produces a set of 14 variables, many of them still highly inter-correlated, for the discriminant function. A potential defect of MDA is its inability to screen out insignificant variables through significance tests on individual coefficients. Variables which apparently contributed most to the performance of the discriminant function include the interest coverage ratio, earnings variability, interest coverage variability, return on investment, and maintenance and depreciation expense to operating revenues. Some of these variables, however, have coefficients with unexpected signs. The extensive fitting of the data with their model enables it to correctly classify 80%-90% of the bonds. Adopting a holdout sample technique which still has some upward bias (in the selection of independent variables), the model correctly predicts about 76% of the bond classifications correctly. An ability for the model to correctly anticipate rating changes is also found analogous to the linear regressions models. Although the MDA approach to credit ratings settings has some limitations. The most important one is the ordinal ranking of credit ratings. The MDA approach considers each outcome as unique; it does not capture the ordinal nature of credit ratings. Different rating categories for example “AAA” and “A” are not only different, but “AAA” indicates better creditworthiness than an “A” rated issuer.

More recent empirical studies on associating credit ratings data with publicly available information use logistic analysis. The first study to use the ordered probit model in the attribution of credit ratings is by Kaplan and Urwitz (1979), who propose an alternative approach, which takes into account the process of assigning credit ratings. In the rating process, the rating agency tries to measure the risk or PD of bond issues or issuers. Unfortunately, the agency cannot measure default risk on a ratio or interval scale but can only make an ordinal ranking of the bond issues: that is, Aaa bonds are less risky than Aa, which are less risky than A, and so forth. Credit ratings convey ordinal information, so it is unlikely that the rating process will result in equal interval rating groups, which the previous studies based on simple regressions assumed. Secondly, previous studies using MDA leave out some of the available information by assuming that ratings only convey nominal information; MDA also requires multivariate normality for the independent variables and does not have convenient tests of significance. Using an ordered probit model, to handle this situation they distinguish between the dependent variable of theoretical interest, and the observed dependent variable.

Consistent with previous studies, they select Moody’s rated industrial bonds with unchanged ratings in the year 1971-72. In addition to this sample, they collect data for a second sample consisting of all new industrial issues rated by Moody's between 1970 and 1974. The new-issue sample is split up randomly, into an estimation sample of 140 issues and a holdout sample of 67 issues. They use the following company specific financial information: Interest coverage ratios: cash flow before interest and taxes/interest charges (CFBIT/INT); cash flow before interest and taxes/total debt (CFBIT/TD). Capitalization (leverage) ratios: long-term debt/total assets (LTD/TA); long-term debt/net worth (LTD/NW). Profitability ratio: net income/total assets (NI/TA). Size variables: total assets (TA); size of bond issue (IS). Stability variables: coefficient of variation of total assets (CVTA); coefficient of variation of net income (CVNI). A 0-1 dummy variable is included to represent the subordination status (S) of the bond issue. They show that in a simple model using a subordination dummy variable, total assets, one financial ratio and the common stock market beta coefficient can correctly classify about two-thirds of a holdout sample of newly issued bonds.

A more recent study by Blume et al. (1998) use an ordered probit model and further refine and generalizes the method proposed by Kaplan and Urwitz (1979). This is an extension to the first ordered probit model, as they use panel data covering the years 1978-1995 instead of single cross-sections of the firms previously used. Through the use of panel data and the addition of year-dummies, they are able to investigate the existence of continuing stringent standards by rating agency. They also modify their model specification to cater for non-linearity in the relationship between credit ratings and variables such as interest coverage. In addition to financial ratios incorporating a firm’s interest coverage, leverage, profitability and size, they also use market beta coefficient and year dummies. This study shows that part of this decline in the average level of actual bond ratings could be due to the use of more stringent rating standards in assigning ratings. The analysis of a panel of firms over the eighteen years from 1978 through 1995, are consistent with this explanation. The results suggest that if it were not for the use of more stringent rating standards, the level of bond ratings might have actually been higher today than in the past. They correctly predict 57% percent of their ratings. The percentage of correct prediction in lower rated firms is better than for the higher rated firms. The method fails to correctly discriminate between high rated firms within the panel data.

Using Blume et al. (1998) method, Gray et al. (2006) use Australian ratings data from S&P. They document similar results, and suggest that the stringent rating standards by the CRAs are a global phenomenon. From a methodological point of view, the use of logistic approach may have solved issues related to linear specifications. However, studies using ordered probit model fail to correctly discriminate between higher rated firms. The percentage of correct predictions is higher for the lower rated firms compared to higher rated firms. Further research is required to incorporate qualitative and quantitative methods in the attribution of credit ratings. The subjective element and impact of regulatory changes in evaluating credit ratings, alongside financial aspects, has not been touched upon in the literature so far.

3.2.2 Credit Ratings and Issuer Governance Structure

Previous literature on the determinants of credit ratings exclusively focuses on the use of financial and accounting information. A firm's credit rating reflects a rating agency's opinion of an entity's overall creditworthiness. Moreover, rating agencies also have access to data confidential to the firm. The agencies conduct an analysis of the firm based on management interviews and overall business and industrial risk factors. Credit ratings are also concerned with firm governance, as weak governance structure can lead to a poor financial position, and leave debt holders vulnerable to losses. S&P's[44] and Fitch[45] rating services issued a framework to assess firm's governance. This shows the potential importance of governance in relation to the analysis of a firm's overall credit worthiness.

The first study to explore governance related issues in a credit rating scenario is Bhojraj and Sengupta (2003). They use a sample of 1005 industrial bond issues over 1991-96, incorporating a set of financial and risk factors as control variables (many of which have previously been used in the literature). In addition they employ two additional governance related variables to explain credit ratings, namely: the percentage of the company's common stock held by institutions, and the percentage of the board of directors who are not also officers of the firm. They conclude that firms with a higher percentage of outside directors on the board and with greater institutional ownership enjoy higher ratings. This study provides an initial

[44] Standard & Poor's, 2002. S&P's Corporate Governance Scores: Criteria, Methodology and Definitions. McGraw-Hill Companies, Inc., New York.

[45] Fitch, 2004. Credit policy special report, evaluating corporate governance: the bondholder's perspective, New York.

framework for researchers to further study governance related factors in determining credit quality.

Ashbaugh et al. (2006) further extend the relationship of governance factors to credit ratings and provide a more comprehensive relationship between governance and credit ratings. Using S&P's governance framework[46], they quantify each clause and present their framework using a broader range of governance factors to Bhojraj and Sengupta (2003). As such, they provide a more comprehensive view of the relationship of governance factors to credit ratings. They discuss four dimensions of governance factors based on S & P's published framework, providing empirical proxies to capture these major attributes of governance. These four dimensions cover the following: Ownership structure and influence; Financial stakeholder's rights and relations; financial transparency and board structure and processes. Using an ordered logit model specification, they show that firm credit ratings are: negatively associated with the number of block holders that own at least a 5% ownership in the firm; positively related to weaker shareholder rights in terms of takeover defences, positively related to the degree of financial transparency; positively related to overall board independence, board stock ownership and board expertise, and negatively related to CEO power on the board. They conclude that firm's governance affects firms' credit ratings.

The two studies mentioned above associate credit ratings with governance. The predicted model signs other then G-Score suggested by Gompers et al. (2003) also are the same as prior expectations. The positive relationship between the governance and ratings identifies the potential for future research in two directions. One aspect not covered in these studies is whether the addition of governance related factors improves overall prediction of credit ratings? The second issue is that the positive relationship between governance related factors and credit rating shows that further research may associate other subjective factors to ascertain credit ratings.

3.2.3 Credit Ratings and Criticism of Credit Rating Agencies

CRAs are criticized for having a conflict of interest in the credit rating process. A potential conflict of interest exists when a credit rating agency has an economic

[46] Please refer to footnote 41

interest in basing a credit rating on anything other than an issuer's creditworthiness. IOSCO (2003) states that: "Perhaps the single greatest concern facing CRA's is identifying and addressing potential and actual conflicts of interest that may inappropriately influence the rating process." CRAs acknowledge both the existence of potential conflicts, and the fact that clear (and consistently enforced) structures and procedures must be in place to counteract them. Thus, the debate is not over whether these potential conflicts exist, but over whether the agencies are managing them adequately.

The first paper that provides a comprehensive test of whether well-known conflicts of interest at bond rating agencies influence their actions is by Covitz and Harrison (2003). They hypothesize that if conflicts of interest strongly influence CRAs, then CRAs should be slower in issuing credit rating downgrades for their clients, especially when they downgrade them from, investment to non-investment grade. They investigate this hypothesis using a new data set of about 2000 credit rating migrations from Moody's and S&P, and a matching sample of issuer-level bond prices. The authors conclude that reputational incentives, not conflicts of interest, influence the CRAs. Specifically, they find that any market anticipation of credit rating changes is less for large issuers and issuers that fall from investment grade to non-investment grade. Their study finds no real evidence which is consistent with rating agencies acting in the interests of issuers due to a conflict of interest. Instead, rating agencies appear to be relatively responsive to reputational concerns and so protect the interests of investors. Their results also show what is statistically discernible, on average, and thus cannot completely rule out the possibility that in some instances rating agencies have acted in the interests of issuers. The authors do acknowledge that their reliance on monthly (verses daily) spread data reduces the statistical power of the analysis.

Regulation FD was promulgated by SEC on October 23, 2000. The regulation prohibits US public companies from making selective, non-public disclosures to favoured investment professionals. The regulation provides a conditional exception for information disclosed to rating agencies, provided that the information is used solely to prepare a credit rating. CRAs state that this unique access facilitates and improves the credit rating process, even though it makes no difference to their process as they already had access to confidential information. The exemption also benefits issuers, as it allows them to disclose freely to the agency without violating the regulation.

This particular regulation is investigated in the literature by Jorion, Liu, and Shi (2005). They view Regulation FD as a development that potentially increases the information value of credit ratings, since following the introduction of Regulation FD, equity analysts working in other investment houses have no access to companies' confidential information. They examine the effect of credit rating changes on stock prices in the period pre-and post-regulation. Their sample consists of 1,767 downgrades and 437 upgrades. Approximately 90% of the rating changes are from Moody's and S&P. The remaining 10% of the sample consists of Fitch ratings. The pre-regulation period starts from August 1998 to September 2000, and post-regulation period starts from November 2000 to December 2002. Employing an event study methodology, they compare the stock market reaction to bond rating changes before and after Regulation FD. They conclude that the regulation fair disclosure does alter the informational advantage of rating agencies. The authors state that after Regulation FD, rating agencies became privileged conduits of selective disclosure to the public. They find that the effect of rating changes on stock prices has become more pronounced. Both downgrades and upgrades now have a bigger affect on stock prices.

Amato and Furfine (2004) use an ordered probit model similar to Blume et al. (1998) to study the influence of the state of the business cycle on credit ratings. They use annual data on all U.S. firms rated by S&P between 1981 and 2001, a total of 10,144 observations. They use three sets of information to ascertain credit ratings. These three sets are: firm business risk, financial risk and the business cycle proxies. The business risk is demonstrated by using three distinct variables; namely firm size, market beta and the market model standard error capture the idiosyncratic risk factor. The market beta standard error is estimated by using estimates of the standard error of the residual from the market model. They argue that a firm's market beta demonstrates the overall business risk and its idiosyncratic risk demonstrates factors unique to the firm. The four financial ratios are the same as those used by Blume et al. (1998); interest coverage, operating income to sales, long-term debt/assets and total assets. They use three measures to demonstrate the state of the economy during their sample period. The first indicator captures recessions and expansions using recession dummies by following NBER dates. Their second measure is the output growth gap defined as difference between real GDP growth and potential GDP growth. The last measure of the state of the business cycle is the discrete-valued indicator of the relative rate of current real GDP growth. The third measure is constructed by using a histogram of annual real GDP growth rates for the entire sample period. If the current quarterly observation of annual growth falls into the lower third of this distribution, the indicator is assigned a value of -1, a 0 if it falls in the middle third and a 1 if it falls in the upper third. Their empirical results suggest that ratings do not generally exhibit excess sensitivity to the business cycle. However, they detect procyclicality in ratings when they use investment grade ratings only or newly assigned ratings.

The major reason underpinning the fact there is a paucity of literature on the subjective element involved in the rating process is the inherent difficulty involved in quantifying these issues. A further direction not yet explored in the literature is the identification of subjective elements involved in the rating process, and the potential conflict of interest in the overall business structure of rating agencies.

3.3 Data and Methodology

3.3.1 The Sample and Data Sources

The data is collected from a variety of sources using a data window from 1995 through 2009. The final data set constitutes an unbalanced panel covering fifteen years. The selection of fifteen years of data span enables the study to cover a variety of stages in the business cycle[47].We select a portfolio of issuer firms from S&P 500[48],

[47] According to National Bureau of Economic Research (NBER), 2001 recession period lasted for eight month from March 2001 till November 2011, and 2007 lasted for eighteen months starting December 2007 till June 2009.

[48] The S&P 500 has been widely regarded as the best single gauge of the large cap U.S. equities market since the index was first published in 1957. The index has over US$ 4.83 trillion benchmarked, with index assets comprising approximately US$ 1.1 trillion of this total. The index includes 500 leading companies in leading industries of the U.S. economy, capturing 75% coverage of U.S. equities.

S&P 400[49] and S&P 600[50] index constituent firms. We limit our portfolio to these index constituent firms, because the variables we use in our models evidence some limitations in terms of data availability. The data for G-Index is only available for S&P 1500 firms, which is constituted by combining three above mentioned indices: S&P 500, S&P 400 and S&P 600. We consider this to be a representative of the whole universe of corporate issuer firms, as the three indices involve large, medium and small size firms. Based on the availability of credit ratings and other data, our final sample produces an unbalanced panel of fifteen years, consisting of 7234 firm-year observations. From these 7234 observations, we further filter our sample and exclude firms from the financial and utility sectors. Following Blume et al. (1998), we exclude financial and utility sector firms as they work under different regulations, and they have separate rating methodologies from each of S&P and Moody's. After excluding financial and utility firms, our sample drops to 5292 firm-year observations. From this we further exclude firms rated less than B(S&P) or equivalent B (Moody's). The lower category firms are excluded due to two main reasons: First, there are very low number of firms in lower categories, and second, in case of default S&P assigns a rating D, while minimum credit quality for Moody's is C (Comparison of long-term ratings between the two agencies is attached as appendix III). Since the fundamentals of these lower rated firms are significantly different than B category firms, we do not combine lower rated firms with B category in our sample. These initial filters drop our final firm-year observations to 5192 for our empirical analysis.

We have 460 issuer firms in the year 2009, and we track credit ratings history of these firms depending upon the ratings data availability until 1995. This constitutes an unbalanced panel of firm-year observations. However, in the year 2009, our sample of 460 firms excluding financial and utility sectors, we have 274 (60%)

[49] The S&P MidCap 400 provides investors with a benchmark for mid-sized companies. The index covers over 7% of the U.S. equity market, and seeks to remain an accurate measure of mid-sized companies, reflecting the risk and return characteristics of the broader mid-cap universe on an on-going basis.

[50] The S&P SmallCap 600 covers approximately 3% of the domestic equities market. Measuring the small cap segment of the market that is typically renowned for poor trading liquidity and financial instability, the index is designed to be an efficient portfolio of companies that meet specific inclusion criteria to ensure that they are investable and financially viable.

issuers from S&P 500 index, 129 (28%) from S&P 400 index, and 57 (12%) from S&P 600 index.

There are three stages of the data collection: the first involves obtaining data for the credit ratings from S&P and Moody's. We use Compustat through WRDS to extract data for S&P[51] long-term domestic issuer level firms. We use data from Bloomberg to collect long-term issuer level data for Moody's[52] credit ratings data. For both the rating agencies, we assign a rating to each specific firm as on December 31 of each year. As ratings may change during the year, we only consider credit ratings assigned as of end-December. Our portfolio has 1500 companies, but for the analysis, we only consider firms with ratings obtained from both CRAs. Following Beaver at al. (2006), firms in our selected portfolio rated only by one rating agency S&P or Moody's, are not considered for inclusion in the analysis. This is because this study not only determines credit rating factors, but also undertakes a comparative study between the two rating agencies.

Financial and Accounting Variables

The COMPUSTAT annual files are the source of data collection for firm based financial ratios and accounting information. We compute different financial ratios to show a firm's profitability, leverage, coverage and asset quality. Previous studies use different financial ratios to show firm's financial risk. Based on previous literature, we select seven ratios to show firms leverage, coverage and profitability. The two leverage ratios computed in the study are DLTT (long-term debt total) to total assets, and DLTT+DLC (long-term debt total + debt in current liabilities) to Total Assets. Two coverage ratios are selected for each firm, EBITDA (earnings before interest) to XINT (interest charge) and OIADP (operating income after depreciation) to XINT (interest charge). Three profitability measures are computed: OIBDP (operating income before depreciation) to Net Sales, EBITDA (earnings before interest) to sales

[51] The S&P's issuer credit rating is a current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations. This opinion focuses on the obligor's capacity and willingness to meet its long-term financial commitments (those with maturities of more than one year) as they come due.

[52] Moody's credit ratings are opinions of the credit quality of individual obligations or of an issuer's general creditworthiness (without respect to individual debt obligations or other specific securities).They address the possibility that a financial obligation will not be honoured as promised. Such ratings use Moody's Global Scale and reflect both the likelihood of default and any financial loss suffered in the event of default.

and net income (loss) to total assets. Based on previous studies, and understanding of the assignment of ratings, we expect both profitability and coverage to be positively related to credit ratings. Similarly, we expect a negative relationship between a firm’s leverage and its assigned credit rating.

As mentioned above, a number of studies also document a positive relationship between firm size and credit ratings. Using COMPUSTAT annual files to collect values for total assets, we measure firm size by using the natural logarithm of total assets. The value of total assets is also used in the computation of certain profitability measures. We follow previous research by including the equity beta as a measure of systematic risk. Blume et al. (1998), for instance say that a firm will be less able to service its debt for given financial ratios as its equity risk increases. Firm level betas are obtained from CRSP indices/deciles: portfolio assignments. We use the year-end-beta daily file to collect firm level beta values for each year. Company based beta’s are available for NASDAQ and NYSE/AMEX. We expect to see a positive relationship between firm size and credit ratings. The reason behind this expectation is that larger firms tend to be older, with more established product lines and more varied sources of revenues. This in turn will improve the overall creditworthiness of the firm. Similarly, we expect a negative relationship between the firm’s equity beta and its credit rating. Other things equal, we expect firms with higher equity risk to have a lower credit rating.

Governance Variables

In our study, we also use three governance related variables. These three governance related variables are: G-Score as per Gompers et al. (2003), the percentage of the company’s stock held by institutions, and finally, the percentage of the board of directors who are not also officers of the firm. Ashbaugh et al. (2006) state that a key element of sound corporate governance is whether a firm maintains a level playing field for corporate control, whether it is open to changes in management and ownership that provide increased shareholder value. Gompers et al.(2003) construct an index based referred as the G-Score, to measure the power-sharing relationship between investors and management. The 24 provisions are classified into five categories of management power:(1) tactics for delaying hostile bids;(2) voting rights;(3) director/officer protection;(4) other takeover defences; and (5) state takeover laws. Each of these 24 provisions contributes one point towards the total G-Score. A higher G-Score indicates lower shareholders rights and greater management power. We collect data for G-Score from the RiskMetrics-Governance legacy database. These are updated every three years, as changes in governance structure are not very frequent.

Other governance variables used are the percentage of the board of directors who are not also officers of the firm, and the percentage of stock held by institutional investors. We use the RiskMetrics-Directors Legacy database to compute the percentage of the board of directors who are not also officers of the firm. The database starts from 1996 onwards; we have repeated the 1996 percentage in the year 1995. This does not affect our findings, as due to strategic consistency, changes in governance structure are not frequent in corporate environment. The above G-Score database is updated every three years as well, as the reason given behind these three years is the changes in governance structure of a firm is not very frequent. The database maintains annual company director name and their status on board, we compute the percentage of board directors by using information for each director. We use Thomson Reuters-Institutional (13F) holdings-s34 to collect data for stock held by Institutions. The December database for each of the years 1995-2009 is used for our analysis. The database maintains individual institutional investment by name and amount; we add all the reported individual institutional investment to compute our institutional investment. The percentage is computed by using total stock held by institutions and total outstanding stock.

We expect G-Score to have a negative relationship with the credit ratings. We expect firms with greater higher shareholders rights (lower G-Score) are likely to provide effective monitoring and control over management leading to efficient managerial decision making. Similarly, we expect the other two governance variables to exhibit a positive relationship. As greater institutional investment poses greater confidence in credit quality of a firm, similarly a greater number of independent directors on the board are likely to provide more efficient oversight of management.

Other Variables

In our study, we also include different proxies to demonstrate selective criticism and potential subjective elements involved during rating process. The first variable we measure is to observe potential rating shopping behaviour within issuer firms. We use a dummy (1, 0) variable equal to 1 for a firm having three or more ratings and zero otherwise. We assume that firms with more ratings from different rating agencies exhibit rating shopping behaviour. Most of the rating agencies follow an "issuer pays"[53] business model. There is a tendency for rating shopping behaviour from the issuers to obtain desirable credit ratings. The credit rating history of a firm is obtained from Bloomberg. Recall, our initial sample of issuer firms have credit ratings from both the agencies. Within this sample we then use a dummy variable to demonstrate if a firm has more than two ratings. The picture that has emerged from the recent criticism over rating agencies signifies that rating agencies compromise the quality of their rating process to facilitate issuers' interests due to the structure of their business model. Rating agencies argue that such an act would undermine their long-term business growth and would also risk their reputation, which is very important in the rating business. The inclusion of rating shopping dummy in our specification would provide evidence as to whether firms having more than three ratings tend to have better ratings compared to issuer firms relying only on two ratings.

We use a dummy for regulation FD[54]in our model. Jorion et al. (2005) show that after the introduction of regulation FD, the information effect of CRAs on stock prices through the impact of a downgrade and upgrade appears to be much greater. In order to take account of this possible effect, we use a dummy for post- and pre-regulation FD period. A zero dummy variable is used for the pre-regulation FD, and the dummy is set equal to one for the post-FD period. The sign on this dummy variable indicates, if regulation FD initiated any change in the rating agencies approach towards assigning firm ratings. A negative sign would suggest that firms in the post-regulation FD period face a stricter rating agency standards compared to the

[53]All the three big rating agencies follow issuer pay model: Moody's, S&P, and Fitch. Whereas, Egan Jones another NRSRO follows investor pay model.

[54]Promulgated on October 23, 2000 the regulation restricts U.S. public companies from making selective, non-public disclosures to favored investment professionals. It exempts credit rating agencies from the restriction.

pre-regulation FD scenario, by which we mean that firms would obtain a higher rating on the same values for fundamental and governance variables in the pre-regulation FD scenario than in the post-regulation scenario.

We also use a proxy to capture stages in the business cycle. The NBER issues dates for the start and end of recession/boom periods. In our sample from 1995-2009, we observe two major recessions. The first starts in March 2001 and runs to December 2001. The second starts starting in December 2007 and ends in June 2009. We use the annual percentage growth of Gross Domestic Product (GDP) as a proxy for the business cycle. We collect data for GDP growth percentage from the World Bank website, where historical annual data based on calendar year is available for member countries from the year 1981 onwards. S&P maintains that while a key element in credit rating analysis is the evaluation of historical data, ratings opinions are designed to be forward looking[55]. Similarly, Moody's also states that their focus is on fundamental factors that will drive an issuer's long-tem ability to meet debt payments[56]. We do not expect rating agency to follow different rating standards, but a negative (positive) sign would suggest some validity to the criticism they become stricter(lenient) during recession periods.

3.3.2 The Ordered Probit Model

The Current literature examining the association between the allocation of credit ratings and publicly available information uses an ordered probit model. This model associates the dependent variable to observed explanatory variables through an unobserved continuous linking variable. The approach we adopt in this chapter also uses an ordered probit model, specifically that proposed in Hausman et al. (1992) which is implemented in a credit ratings settings by Blume et al. (1998). This study maps financial, governance-related and other variables onto credit ratings. This approach is applicable in a credit rating setting due to the structure of credit ratings; they are discrete and follow a natural ordering. Due to these two distinct qualities,

[55] S&P maintains in its "What Credit Ratings Are & Are NOT" available on www.standardandpoors.com that they take into account not only the present situation but also the potential impact of future events on credit risk. For example, assigning its ratings S&P factors in anticipated ups and downs of business cycles.

[56] Moody's state in their document "How to Get Rated-Moody's" available on www.moodys.com that their ratings are not intended to ratchet up and down with business or supply-demand cycles or to reflect short-term market movements.

the usual least square econometrics techniques are not appropriate. Moreover, as credit ratings possess a natural ordering, multiple discriminant analysis modelling becomes inappropriate.

In an ordered probit model, rating categories map into a partition of the range of the unobserved variable, which is in turn a linear function of the observed explanatory variables. Initially, we run two sets of identical ordered probit regressions, one for Moody's and one for S&P. We define our dependent variables in each set of regressions as the rating category assigned by the relevant rating agency, Moody's or S&P respectively. This rating category is converted into four numerical values for both the agencies, namely 0 to 3. We combine AA (Aa)[57] and AAA (Aaa) into one "highest rating" category. This is done as the sample comprises a low frequency of AAA (Aaa) issuers. We also combine our two low rating categories, BB/B (Ba/B) into one category. We exclude from our sample any issuer rated less than B by either S&P or Moody's. After the exclusion from of our sample of these low rated firms and combining AA/AAA (Aa/Aaa) and BB/B (Ba/B) issuer firms, our data sample has four distinct values: 3 if the company is rated AAA/AA (Aaa/Aa), 2 if the company is rated A (A), 1 if the company is rated BBB (Baa), and finally 0 if the company is rated BB/B (Ba/B). This means that a positive sign on our coefficients can be associated with an improvement in the likelihood of a higher rating and a negative sign with a deterioration in the likelihood of a higher rating.

In the model, we define the following for an issuer i at the end of year t: Y_{it} is the rating category of an issuer i at the end of year t. This Y_{it} can only take the four values given by equation (3.1).

$$Y_{it}=\begin{cases} 0 \text{ if a company=BB/B(Ba/B)} \\ 1 \text{ if a company= BBB(Baa)} \\ 2 \text{ if a company=A (A)} \\ 3 \text{ if a company= AAA or AA(Aaa/Aa)} \end{cases} \tag{3.1}$$

As discussed earlier the values of Y_{it} are censored as they only take one of the four possible values given in our ordered ratings. We relate these credit ratings, converted into ordered numbers, to our explanatory variables by means of the following equation.

[57] Values in parenthesis are for Moody's equivalent credit ratings.

$$Y^*_{it}=X_{it}\beta+\epsilon_{it} \tag{3.2}$$

Where X_{it} is a vector of explanatory variables, β is a vector of coefficients to be estimated, and ϵ_{it} is a standard normal residual. Equation (3.2) tells us that the dependent variable, which is the rating itself, is dependent upon certain quantifiable factors given by a vector of explanatory variables, X_{it} , and unobservable factors, given by ϵ_{it}. The ordered probit model relates the unobserved variable Y^*_{it} to the observed credit rating Y_{it} in equation (3.3) as follows:

$$Y_{it}=\left\{\begin{array}{l} 0 \text{ if } Y^*_{it} \le \propto_1 \\ 1 \text{ if } \propto_1 < Y^*_{it} \le \propto_2 \\ 2 \text{ if } \propto_2 < Y^*_{it} \le \propto_3 \\ 3 \text{ if } Y^*_{it} > \propto_3 \end{array}\right\} \tag{3.3}$$

The probability of a particular set of explanatory variables linked to a particular set of credit ratings is given by equation (3.4):

$$\Pr ob(Y_{it}=j)=\left\{\begin{array}{l} \Pr ob(X_{it}\beta + \varepsilon_{it} \le \alpha_1) \text{ if } j = 0 \\ \text{Prob } (\alpha_{j-1} < X_{it}\beta+\varepsilon_{it} \le \propto_j) \text{ if } j = 1,2 \\ \text{Prob } \left(X'_{it}\beta + \varepsilon > \alpha_3\right) \text{ if } j = 3 \end{array}\right\} \tag{3.4}$$

where $\epsilon_{it} \sim N(0,1)$.

The parameters α_1 and α_2 in equation (3.3) reflect the proportion of the observations in the sample that fall within each rating category. A higher value of α_1 will increase the likelihood of the number of observations that are classified as BB/B or equivalent. A higher value of α_2 will reduce the number of observations that are classified as BBB. These parameters, therefore, depend on the proportion of observations in the sample that fall into each of the four rating categories. Equation (3.4) implies that higher values of the linear combination of explanatory variables, $X'_{it}\beta$ imply that a higher credit quality is more likely. The value of j that maximises equation (3.4) is the most probable bond rating category, conditional on vector α.

In an ordered probit model, it is difficult to interpret the economic significance of the size of the estimated coefficients simply by looking at the estimated coefficients. In an attempt to extract the strength and impact of each explanatory variable on our dependent variable, we also report the product of the estimated coefficient and the corresponding standard deviation (across all observations).This column informs us about the change in the conditional expectation of Y_{it} in reply to a change of one standard deviation in the value of the explanatory variable. This also helps us to compare the relative importance and affect of each variable between the two agencies.

As suggested by Blume et al. (1998), we also use a comparison of the most probable ratings (suggested by the model specification) to the actual ratings in order to assess the goodness-of-fit of the probit model. We estimate three models for each rating agency. First (Model 1), we estimate a model based only on financial and accounting information, and estimate the most probable ratings. Second, we add three governance-related variables by controlling for financial and accounting information based variables. This constitutes our Model 2. Once again, we estimate the most probable credit rating after adding these governance related variables, and observe whether the governance-related variables add any additional explanatory predictive power to our overall rating regressions. Third, we add our set of three variables demonstrating potential criticism and subjectivity involved in the rating process. After adding these variables to this Model 3, we re-estimate the predicted ratings. The improvement in prediction power informs us about the goodness-of-fit of our model. To further aid in analysis of subsequent improvement in prediction power of our three models, we also report the log likelihood, LR χ^2 and pseudo (McFadden's) R^2 of the three models.

As mentioned in the data section, we have computed several financial ratios to demonstrate issuer firm's profitability, leverage and coverage. In order to avoid multicollinearity issues, we first prepare a variance covariance matrix. Second, we estimate VIF scores to capture potential multicollinearity. Implementing these two steps, we drop variables having high correlation.

Finally, we find our coverage measure is highly skewed. This issue is also mentioned in Blume et al. (1998) and in response, they truncate the coverage ratio to eliminate extreme values. Following their method, we truncate our coverage ratio in two steps: First, any interest coverage ratio less than zero is set to zero, and second any number higher than 50 is set to 50. Out of 5192 observations, 76 observations are less than zero and 178 observations are higher than 50. Blume et al. (1998) show that an interest coverage change: from 0 to 5 tends to be more informative, and the negative value provide no additional information. Similarly, a higher level of coverage ratios provides no additional information to ascertain credit ratings.

The use of panel data also raises questions on the existence of additional normally distributed cross-section error. As a robustness check, we also estimate our final model (with all explanatory variables) with a random-effects ordered probit model to cater for issuer specific cross-section errors. We model the issuer-specific error, which in practical terms implies adding time averages of the explanatory variables as additional time-invariant regressors. This serves as additional test on the interpretation of our initial results based on ordered probit model.

3.4 Empirical Results

Our empirical evidence begins with a descriptive analysis of our sample. We then report our results based on the three estimated models. As a goodness-of-fit measure, we employ prediction success matrices to observe the performance of each model. Finally, we present the results of using an alternative method using random-effects ordered probit model, to analyse the data.

3.4.1 Descriptive Statistics

Table 3.1 reports the descriptive statistics relating to the frequency and percentage distribution of our 5192 firm-year observations. From table 3.1, we see that during the sample time period, the frequency of highly rated firm is falling as a percentage of overall observations in a particular year. In 1995, consider the AA/AAA category, in the case of S&P we have 17.92% of firms in the highest rating category, with 12.74% in Moody’s, but this number falls to 7.57% in the case of S&P and 6.41% for Moody’s by 2009. Moreover, in both the rating agencies, we observe that in 1995, firms in the BB/B category account for only around 16% of the sample, but this number increases to 27.81% in case of S&P and 31.22% in case of Moody’s by 2009. This shows that overall; both the rating agencies are assigning firms to lower ratings categories in the later years of the data sample as compared to assignments in earlier years.

If we compare the two CRAs, we observe that through our data window Moody's is generally placing firms in a lower category as compared to the assigned ratings of S&P. As our sample only consists of firms with ratings from both the rating agencies, in general firms are rated lower by Moody's compared to S&P.

Table 3.2 reports the frequency distribution of our sample in terms of different industrial sectors. Our data sample excludes firms from the financial and utility sectors. Based on the GICS[58] classification, our sample of 5192 observations is distributed over eight industrial sectors. We observe that other than the Information Technology sector, in all other industrial sectors, Moody's has higher frequency of observations in the lower rating category. The Industrial sector has the highest frequency of 1159 firm-year observations and telecommunication has the lowest frequency of 88 firm-year observations.

[58] Global industry classification standard (GICS) is developed by S&P and MSCI Barra, GICS consists of 10 sectors, 24 industry groups, 68 industries and 154 sub-industries.

Table 3.1 Frequency/Percentage Distribution of Observations Over Time

The table reports the descriptive statistics for our sample of 5192 observations over time 1995-2009. The reported table is classified by credit ratings from S&P and Moody’s. Panel A reports frequency of observations over time from S&P, and panel B reports same for Moody’s. First column is each rating category reports the frequency and second column reports the percentage of category in total observations.

	BB/B		BBB		A		AA/AAA		Total
Panel A: S&P Frequency(%Percentage) of Rating Categories Over Time									
1995	34.00	16.04%	58.00	27.36%	82.00	38.68%	38.00	17.92%	212.00
1996	34.00	15.45%	63.00	28.64%	86.00	39.09%	37.00	16.82%	220.00
1997	32.00	14.16%	70.00	30.97%	89.00	39.38%	35.00	15.49%	226.00
1998	49.00	17.44%	98.00	34.88%	100.00	35.59%	34.00	12.10%	281.00
1999	56.00	19.24%	108.00	37.11%	96.00	32.99%	31.00	10.65%	291.00
2000	64.00	20.78%	119.00	38.64%	98.00	31.82%	27.00	8.77%	308.00
2001	64.00	20.45%	127.00	40.58%	96.00	30.67%	26.00	8.31%	313.00
2002	99.00	27.73%	139.00	38.94%	94.00	26.33%	25.00	7.00%	357.00
2003	106.00	29.36%	135.00	37.40%	96.00	26.59%	24.00	6.65%	361.00
2004	125.00	30.86%	157.00	38.77%	102.00	25.19%	21.00	5.19%	405.00
2005	128.00	30.99%	159.00	38.50%	106.00	25.67%	20.00	4.84%	413.00
2006	154.00	34.84%	172.00	38.91%	97.00	21.95%	19.00	4.30%	442.00
2007	163.00	36.22%	174.00	38.67%	95.00	21.11%	18.00	4.00%	450.00
2008	163.00	35.98%	182.00	40.18%	90.00	19.87%	18.00	3.97%	453.00
2009	173.00	37.61%	179.00	38.91%	88.00	19.13%	20.00	4.35%	460.00
Total	1444.00	27.81%	1940.00	37.37%	1415.00	27.25%	393.00	7.57%	5192.00
Panel B: Moody's Frequency/Percentage of Rating Categories Over Time									
1995	33.00	15.57%	66.00	31.13%	86.00	40.57%	27.00	12.74%	212.00
1996	36.00	16.36%	68.00	30.91%	91.00	41.36%	25.00	11.36%	220.00
1997	35.00	15.49%	75.00	33.19%	89.00	39.38%	27.00	11.95%	226.00
1998	60.00	21.35%	99.00	35.23%	98.00	34.88%	24.00	8.54%	281.00
1999	65.00	22.34%	105.00	36.08%	96.00	32.99%	25.00	8.59%	291.00
2000	75.00	24.35%	107.00	34.74%	100.00	32.47%	26.00	8.44%	308.00
2001	77.00	24.60%	116.00	37.06%	98.00	31.31%	22.00	7.03%	313.00
2002	112.00	31.37%	133.00	37.25%	88.00	24.65%	24.00	6.72%	357.00
2003	117.00	32.41%	137.00	37.95%	86.00	23.82%	21.00	5.82%	361.00
2004	140.00	34.57%	153.00	37.78%	91.00	22.47%	21.00	5.19%	405.00
2005	150.00	36.32%	151.00	36.56%	92.00	22.28%	20.00	4.84%	413.00
2006	171.00	38.69%	160.00	36.20%	91.00	20.59%	20.00	4.52%	442.00
2007	176.00	39.11%	172.00	38.22%	84.00	18.67%	18.00	4.00%	450.00
2008	180.00	39.74%	171.00	37.75%	85.00	18.76%	17.00	3.75%	453.00
2009	194.00	42.17%	166.00	36.09%	84.00	18.26%	16.00	3.48%	460.00
Total	1621.00	31.22%	1879.00	36.19%	1359.00	26.17%	333.00	6.41%	5192.00

Table 3.2 Frequency/Percentage Distribution of Observations Rating Class and Industry Classification

The table reports the descriptive statistics for our sample of 5192 observations over eight GICS sectors. The reported table is classified by credit ratings and excludes financial and utility firms. Panel "A" reports frequency of observations over GICS industrial sectors from S&P, and panel "B" reports same for Moody's. In each rating category, first column displays the frequency, and the second column displays the percentage.

	BB/B		BBB		A		AA/AAA		Total
Panel A: Number of Observations by GICS Industry Classification(S&P)									
Energy	179	34.82%	204	39.69%	108	21.01%	23	4.47%	514
Materials	172	26.06%	285	43.18%	179	27.12%	24	3.64%	660
Industrial	265	22.86%	428	36.93%	345	29.77%	121	10.44%	1159
Consumer Discretionary	413	36.97%	416	37.24%	261	23.37%	27	2.42%	1117
Consumer Staples	64	12.08%	161	30.38%	222	41.89%	83	15.66%	530
Health	164	25.71%	236	36.99%	144	22.57%	94	14.73%	638
Information Technology	168	34.57%	179	36.83%	124	25.51%	15	3.09%	486
Telecommunications	19	21.59%	31	35.23%	32	36.36%	6	6.82%	88
Total	1444	27.81%	1940	37.37%	1415	27.25%	393	7.57%	5192
Panel B: Number of Observations by GICS Industry Classification(Moody's)									
Energy	197	38.33%	195	37.94%	99	19.26%	23	4.47%	514
Materials	185	28.03%	273	41.36%	187	28.33%	15	2.27%	660
Industrial	307	26.49%	422	36.41%	326	28.13%	104	8.97%	1159
Consumer Discretionary	474	42.44%	388	34.74%	229	20.50%	26	2.33%	1117
Consumer Staples	79	14.91%	148	27.92%	230	43.40%	73	13.77%	530
Health	211	33.07%	225	35.27%	129	20.22%	73	11.44%	638
Information Technology	150	30.86%	190	39.09%	131	26.95%	15	3.09%	486
Telecommunications	18	20.45%	38	43.18%	28	31.82%	4	4.55%	88
Total	1621	31.22%	1879	36.19%	1359	26.17%	333	6.41%	5192

In table 3.3 and 3.4, we present descriptive statistics by rating category for a range of financial and governance variables. The two tables present descriptive statistics based on the classification of rating categories from both the rating agencies. The final set of variables is based on the overall descriptive statistics for the entire sample. We observe that in all the data, we have a higher standard deviation relative to the mean in the case of coverage measure. This is due to the higher variation of interest charge across our selected data window. Other variables with a higher standard deviation relative to their mean are the size measure and G-Score. The profitability measure has negative skewness and higher kurtosis values. Our sample consists of firms from S&P500, S&P400, and S&P 600 indices, and higher variation is observed mainly in lower rated firms. Any negative minimum profitability values indicate that the firm has reported a loss in a given year. In terms of leverage factors, we observe that the minimum value of our leverage measure is also zero. This indicates that the particular firm has reported zero long-term debt, and we only use long-term debt in our analysis. We find high skewness and kurtosis in the profitability measure for lower rated firms for both the rating agencies. This is due to the fact that most of the lower rated firms are from the S&P 600 index. For both rating agencies, we observe that skewness and kurtosis are very close to the normal distribution values in the two higher rating categories (A and AA/AAA).

These tables 3.3 and 3.4 present descriptive statistics in groups based on rating categories as well as for the whole sample. We observe the same overall trend for both the rating agencies, but there is slight difference in the levels of these ratios. In terms of financial ratios, our descriptive statistics demonstrate a monotonic relationship between the credit ratings and the financial variables. For instance, our size measure, which is calculated as the log of total assets, is increasing as we proceed to higher-rated credit ratings. Similarly, the mean and median values of coverage and profitability are higher for higher-rated firms. This trend can be observed for both the rating agencies. In terms of the size measure, we observe that Moody’s has very close mean and median values for two lower rating categories, with a slightly higher value difference in the two higher rating categories. We also present the t-Tests (Wilcoxon Mann-Whitney tests) for differences in means (medians) between S&P and Moody’s, the significance level shown in the tables is the difference in means (medians) between table 3.3 and 3.4.

The mean and median of market beta and leverage values decreases across rating categories going from BB/B to AA/AAA. In our study, the leverage measure is estimated using only long-term debt to total assets. We also measure another leverage factor, namely long-term debt plus short-term debt to total assets. As opposed to the three other financial variables, in the case of the leverage measure and the beta measure, we find that the mean and median values are very close to each other in both the rating agencies. For instance, the median values of our leverage factor from lower rating to higher rating category in case of S&P are 0.31, 0.22, 0.17 and 0.13, and in case of Moody’s are 0.30, 0.21, 0.17 and 0.12. We also do not find any significant differences in terms of market beta values between the two rating agencies. This also suggests that firms with same level of leverage and market beta would be assigned similar ratings by the two rating agencies. In terms of statistical significance in differences in means (medians), we do not find much difference between the two samples presented by ordered S&P ratings and ordered Moody’s ratings shown in table 3.3 and 3.4. In financial information, we find statistically significant means (median) of BBB (Baa) category in selected coverage and leverage measure, whereas in A (A) and AA/AAA (Aa/Aaa) category we find size measure significant at 5% and 1%level. This shows that the fundamentals are not very important in determining differences in assigned ratings between Moody’s and S&P.

In addition to the financial variables we now discuss the sample descriptive statistics for the governance variables used in the study. Three governance variables are used, and we observe a monotonic relationship between credit ratings and the governance variables in two variables: the percentage of institutional investment and the percentage of outside directors. In both the rating agencies, the mean and median values are higher for higher ordered credit ratings, and lower for lower rated firms. As observed in the case of financial variables, for two of the governance variables, the mean and median values are higher for Moody’s. The mean value of percentage of institutional investment in a AA/AAA S&P rating category is 0.72, whereas

Moody's has a mean value of 0.74. We do not observe a significant difference between these two governance variables within the two rating agencies.

In terms of our third governance variable, G-Score, we observe different trends between the two agencies. In case of S&P, the mean value is increasing as we go up the ordered ratings. However, median value for the highest two rating categories, on the basis of S&P ratings, are similar. Moody's highest median value is given to a rating category of A with a median of 11, whereas median value is 10 for a Aa/Aaa rated firms. The mean values increase from Ba/B category to A, but we have lower mean value in case of Aa/Aaa rating category. We also observe that the median value in Moody's of a Baa firm is equivalent to a firm in Aa/Aaa category. The median value is lowest in case of a firm in Ba/A rating category.

In terms of statistical significance of differences in means (medians) between samples explained by S&P and Moody's ratings, we find more profound differences between the two CRA's in governance variables. These differences are more visible in two higher categories A(A) and AA/AAA(Aa/Aaa), where we find the differences in means (medians) of institutional investment and percentage of outside directors between the two agencies to be statistically significant. In terms of the third governance variable, G-Score, we do not find statistically different results between two agencies. The significance of two higher categories in governance related variables shows that the two agencies have different standards in allocating credit ratings. We further discuss the significance of these differences, when we discuss our results for ordered probit model in our empirical analysis section.

Table 3.3 Descriptive Statistics based upon S&P's Credit Ratings

The table presents summary descriptive statistics for our eight selected variables distributed on the basis of S&P's ordered credit ratings. These variables are based on financial information of the company and also include three governance related variables. t-Tests (Wilcoxon Mann-Whitney tests) are performed to test the differences in the variable mean (medians) between the data sorted by Moody's ordered credit ratings and S&P's ordered credit ratings. Whole sample data is same for both the agencies, we do not perform the difference of mean (median) test.

	Mean	Median	Standard Deviation	Skewness	Kurtosis	Min.	Max.
BB/B							
Size Measure(LogAssets)	7.81	7.72	0.98	0.24	3.28	4.52	12.50
Market Beta	1.32	1.26**	0.64	0.62	3.79	-0.14	4.28
Coverage Measure	6.55	4.33	6.71	2.35	8.42	0.00	30.75
Leverage Measure	0.32	0.31	0.18	1.13	6.37	0.00	1.20
Profitability Measure	0.02	0.03	0.10	-4.04	37.14	-1.22	0.45
G-SCORE	9.10	9.00	2.52	0.15	2.48	3.00	15.00
% Institutional Investment	0.63	0.63	0.17	-0.59	3.14	0.06	0.98
% of Outside Directors	0.60	0.62	0.17	-0.89	3.90	0.02	1.00
BBB							
Size Measure(LogAssets)	8.49	8.38	1.09	0.42	2.92	5.46	12.63
Market Beta	1.04	0.99	0.50	0.78	4.50	-0.55	3.68
Coverage Measure	10.71**	7.96***	9.29	2.12	7.72	0.00	50.00
Leverage Measure	0.23	0.22**	0.12	0.39	3.10	0.00	0.66
Profitability Measure	0.05	0.05	0.06	-3.03	37.83	-0.85	0.45
G-SCORE	10.10	10.00	2.53	-0.08	2.46	3.00	16.00
% Institutional Investment	0.68	0.70*	0.17	-0.87	3.59	0.10	0.98
% of Outside Directors	0.68	0.72	0.17	-1.11	4.23	0.03	1.00
A							
Size Measure(LogAssets)	9.04**	8.89	1.18	0.50	2.77	6.29	12.56
Market Beta	0.94	0.92	0.40	0.48	3.51	-0.19	2.56
Coverage Measure	17.73	13.67	12.19	1.44	4.25	0.00	50.00
Leverage Measure	0.18	0.17	0.11	0.59	3.50	0.00	0.68
Profitability Measure	0.08	0.07	0.05	0.75	8.16	-0.28	0.35
G-SCORE	10.15	11.00	2.66	-0.36	2.74	3.00	16.00
% Institutional Investment	0.69***	0.70*	0.17	-0.52	2.96	0.15	0.98
% of Outside Directors	0.77***	0.80**	0.16	-0.75	2.96	0.16	1.00
AAA							
Size Measure(LogAssets)	9.84***	9.69	1.31	0.41	3.28	7.10	13.59
Market Beta	0.84	0.83	0.35	0.47	3.48	0.00	2.20
Coverage Measure	24.83	19.91	15.60	0.46	1.85	0.55	50.00
Leverage Measure	0.14	0.13	0.09	0.81	3.86	0.00	0.48
Profitability Measure	0.10	0.10*	0.05	0.04	3.45	-0.07	0.27
G-SCORE	10.37**	11.00**	2.66	-0.22	2.25	5.00	15.00
% Institutional Investment	0.72***	0.72**	0.15	-0.18	3.27	0.21	0.98
% of Outside Directors	0.80***	0.85***	0.16	-0.81	3.21	0.22	1.00

All							
Size Measure(LogAssets)	8.56	8.41	1.25	0.52	3.34	4.52	13.59
Market Beta	1.08	1.01	0.53	0.93	4.79	-0.55	4.28
Coverage Measure	12.53	8.86	11.56	1.75	5.64	0.00	50.00
Leverage Measure	0.23	0.21	0.15	1.25	7.21	0.00	1.20
Profitability Measure	0.05	0.06	0.08	-3.67	44.34	-1.22	0.45
G-SCORE	9.86	10.00	2.62	-0.10	2.45	3.00	16.00
% Institutional Investment	0.67	0.68	0.17	-0.64	3.28	0.06	0.98
% of Outside Directors	0.69	0.71	0.18	-0.74	3.59	0.02	1.00

Note: Financial variables included are based on firm's financial information: These include coverage measure-earnings before interest (EBITDA) to interest charge, leverage measure-long-term debt(DLTT) to total assets (TA), profitability measure - net income to total assets, and size measure-log of assets. Market beta is based on beta value of firm movement compared to NASDAQ/NYSE. We use three governance related variables, G-Score based on Gompers et al.(2003), percentage of Institutional Investment in firm's common stock, and percentage of firm's outside directors on board.
***,**,* indicate significance level at 1%, 5%, and 10% respectively.

Table 3.4 Descriptive Statistics based upon Moody's Credit Ratings

The table presents summary descriptive statistics for our eight selected variables distributed on the basis of Moody's ordered credit ratings. These variables are based on financial information of the company and also include three governance related variables. t-Tests (Wilcoxon Mann-Whitney tests) are performed to test the differences in the variable mean (medians) between the data sorted by Moody's ordered credit ratings and S&P's ordered credit ratings. Whole sample data is same for both the agencies, we do not perform the difference of mean (median) test.

	Mean	Median	Standard Deviation	Skewness	Kurtosis	Min.	Max.
Ba/B							
Size Measure(LogAssets)	7.83	7.72	0.97	0.25	3.22	4.52	12.50
Market Beta	1.27	1.20**	0.63	0.70	3.88	-0.14	4.28
Coverage Measure	6.42	4.48	6.44	2.70	11.25	0.00	50.00
Leverage Measure	0.31	0.30	0.17	1.22	6.79	0.00	1.20
Profitability Measure	0.02	0.04	0.10	-4.14	40.27	-1.22	0.45
G-SCORE	9.20	9.00	2.53	0.14	2.47	3.00	15.00
% Institutional Investment	0.64	0.63	0.16	-0.64	3.13	0.06	0.89
% of Outside Directors	0.59	0.62	0.17	-0.90	3.84	0.02	1.00
Baa							
Size Measure(LogAssets)	8.53	8.40	1.09	0.46	2.93	5.46	12.63
Market Beta	1.05	1.00	0.49	0.78	4.53	-0.55	3.68
Coverage Measure	11.45**	8.44***	9.68	2.00	7.17	0.00	50.00
Leverage Measure	0.22	0.21**	0.12	0.41	3.06	0.00	0.66
Profitability Measure	0.05	0.05	0.07	-3.07	38.10	-0.85	0.45
G-SCORE	10.12	10.00	2.58	-0.08	2.47	3.00	16.00
% Institutional Investment	0.67	0.69*	0.17	-0.78	3.35	0.10	0.93
% of Outside Directors	0.68	0.73	0.16	-1.11	4.22	0.03	1.00
A							
Size Measure(LogAssets)	9.10**	8.98	1.14	0.48	2.88	6.29	12.56
Market Beta	0.94	0.90	0.41	0.51	3.70	-0.19	2.77
Coverage Measure	18.07	14.02	12.31	1.39	4.11	0.00	50.00
Leverage Measure	0.18	0.17	0.11	0.61	3.51	0.00	0.61
Profitability Measure	0.08	0.07	0.05	0.52	8.13	-0.28	0.35
G-SCORE	10.28	11.00	2.62	-0.40	2.84	3.00	16.00
% Institutional Investment	0.70***	0.71*	0.16	-0.54	3.14	0.15	0.98
% of Outside Directors	0.78***	0.82**	0.16	-0.89	3.38	0.16	1.00
Aa/Aaa							
Size Measure(LogAssets)	9.97***	9.93*	1.37	0.22	3.12	6.86	13.59
Market Beta	0.86	0.84	0.36	0.45	3.34	0.00	2.20
Coverage Measure	25.79	21.54	15.68	0.33	1.73	2.18	50.00
Leverage Measure	0.14	0.12	0.10	0.98	3.79	0.00	0.48
Profitability Measure	0.11	0.11*	0.05	0.08	2.95	-0.03	0.27
G-SCORE	9.83**	10.00**	2.65	-0.24	2.11	4.00	14.00
% Institutional Investment	0.74***	0.74**	0.15	-0.29	3.33	0.28	0.98
% of Outside Directors	0.84***	0.87***	0.15	-0.76	2.50	0.45	1.00

All							
Size Measure(LogAssets)	8.56	8.41	1.25	0.52	3.34	4.52	13.59
Market Beta	1.08	1.01	0.53	0.93	4.79	-0.55	4.28
Coverage Measure	12.53	8.86	11.56	1.75	5.64	0.00	50.00
Leverage Measure	0.23	0.21	0.15	1.25	7.21	0.00	1.20
Profitability Measure	0.05	0.06	0.08	-3.67	44.34	-1.22	0.45
G-SCORE	9.86	10.00	2.62	-0.10	2.45	3.00	16.00
% Institutional Investment	0.67	0.68	0.17	-0.64	3.28	0.06	0.98
% of Outside Directors	0.69	0.71	0.18	-0.74	3.59	0.02	1.00

Note: Financial variables included are based on firm's financial information: These include coverage measure-earnings before interest (EBITDA) to interest charge, leverage measure-long-term debt(DLTT) to total assets (TA), profitability measure - net income to total assets, and size measure-log of assets. Market beta is based on beta value of firm movement compared to NASDAQ/NYSE. We use three governance related variables, G-Score based on Gompers et al.(2003), percentage of Institutional Investment in firm's common stock, and percentage of firm's outside directors on board.
***,**,* indicate significance level at 1%, 5%, and 10% respectively.

3.4.2 Empirical Analysis

We begin our empirical analysis by reporting the correlation matrix between our set of variables in table 3.5 and VIF scores for our computed financial and governance variables in table 3.6. These variables can be divided into sets of different groups to demonstrate the firm's level of size, profitability, coverage, leverage, governance and overall market risk. Based on the results of table 3.5 and 3.6, we drop variables having high correlation in order to minimize multicollinearity problems. For our final regressions, we only have one variable to demonstrate a firm's size and market risk, and both of these are used in our regression models.

In the cases of coverage, leverage and profitability ratios we compute more than one financial ratio for each category. We observe that the correlation between the two coverage measures is 0.85 and statistically significant, so we only select one coverage measure for our final analysis.

Similarly, our leverage measures also show high degree of correlation of 0.92, and we only consider one measure in our final regressions. We select our first leverage measure for our final analysis, as the second leverage measure includes short-term debt. Short-term debt is mainly used in a firm to conduct its day to day business, and it remains fairly constant over time. In our initial stage, we estimate three profitability measures. Our second profitability variable, measured as EBITDA to sales shows a higher degree of correlation with our first profitability variable, Operating Income before depreciation (OIBDP) to sales, so we drop it. Our third profitability measure is net income to total assets and shows a correlation of 0.35 with the first measure estimated as Operating Income before depreciation (OIBDP). In our final analysis, we drop our third measure of profitability, as we do not obtain any improvement in explanatory power of our model by keeping both the profitability measures. Secondly, we prefer first measure, as it considers income against sales, whereas the third one again considers total assets. Since, we are also using total assets in our leverage variable; we prefer to use sales figures instead of total assets as it captures a different aspect.

Our correlation matrix presented in table 3.5 indicates that all the three governance related variables have a very low correlation. We include all the three variables in our final analysis, as the correlation between the three variables is low, and each variable captures different governance related information.

In table 3.6, we present variance inflation factor (VIF) scores where panel A uses all the computed variables. We observe that coverage and leverage measure show high VIF scores. In Panel B we only consider one financial ratio to demonstrate firm's coverage, leverage and profitability. The total mean VIF score for the panel B variables is 1.26, and we do not observe any variable with the higher VIF score than 2. This shows that our final variables used in our model are not affected by multicollinearity.

Empirical discussion is based on our ordered probit models and is contained in three sections. The initial section discusses the estimates of the ordered probit model obtained when we use financial and accounting variables only, and we term this specification model one. In the second section, we discuss our model estimates derived using our three selected governance variables in addition to our financial variables as control variables. In our final section, we incorporate the set of variables associated with credit ratings, selective criticism and relevant changes in regulations along with our governance and financial variables. In each section, we also discuss the prediction success matrix and sequential improvements to the estimates from adding additional variables. Finally, we discuss the robustness of our empirical findings.

Table 3.5 Correlation Matrix for Financial and Governance Variables

The table presents the correlation between pairs of variables to be used in our ordered probit models. We short-list our variables based on the correlation matrix, as we only select those variables which are not highly correlated. We calculated two variables each for our coverage and leverage measures, whereas three measures were used to show profitability. The sample consists of 5192 observations spanning fifteen years of data 1995-2009.

	Size Measure (Logassets)	Market Beta	Coverage Measure 1	Coverage Measure 2	Leverage Measure 1	Leverage Measure 2	Profitability Measure 1	Profitability Measure 2	Profitability Measure 3	G-Score	% Institutional Investment	% of Outside Directors
Size Measure (Log assets)	1											
Market Beta	-0.0694***	1										
Coverage Measure 1	0.1892***	-0.0916***	1									
Coverage Measure 2	0.1565***	-0.0763***	0.8539***	1								
Leverage Measure 1	-0.1628***	0.0193	-0.5373***	-0.4493***	1							
Leverage Measure 2	-0.0963***	-0.0204	-0.5397***	-0.4556***	0.9244***	1						
Profitability Measure 1	0.1396***	-0.0831***	0.1815***	0.1477***	0.0593***	0.0489***	1					
Profitability Measure 2	0.1396***	-0.0831***	0.1815***	0.1477***	0.0593***	0.0489***	1***	1				
Profitability Measure 3	0.0632***	-0.1506***	0.4321***	0.3915***	0.2966***	0.2769***	0.3577***	0.3577***	1			
G-Score	0.0208	-0.0554***	-0.0343**	-0.0311**	-0.0335**	-0.0089	-0.0005	-0.0005	-0.0003	1		
% Institutional Investment	0.1156***	0.0067	0.0991***	0.0425***	0.1492***	-0.153***	0.0567***	0.0567***	0.0696***	0.067***	1	
% of Outside Directors	0.3347***	-0.1003***	0.2101***	0.1493***	-0.232***	0.1921***	0.0249**	0.0249*	0.1329***	0.2275***	0.3001***	1

Note: We use three governance related variables. These include G-Score based on Gompers et al.(2003), percentage of Institutional Investment in firm's common stock, and percentage of firm's outside directors on board. Other variables computed are based on firm's financial information: These include coverage measure 1-earnings before interest (EBITDA) to interest charge, coverage measure 2-operating income after depreciation (OIADP) to Interest charge, leverage measure 1-long-term debt(DLTT) to total assets (TA), leverage measure 2-DLTT plus short-term debt(DLC) to TA, profitability measure 1-Opertating Income before depreciation (OIBDP) to sales, profitability measure 2- net income to total assets, and size measure-log of total assets. Market beta is based on beta value of firm’s stock movement against NASDAQ/NYSE indices.

***,**, and * denote statistical significance at the 1, 5, and 10 percent level

Table 3.6 VIF Scores for Financial and Governance Variables

The table presents VIF scores between pairs of variables to be used in our ordered probit model. The sample consists of 5192 observations spanning fifteen years of data 1995-2009, and include financial and governance variables. Panel "A" reports the VIF scores and tolerance for all the variables, and panel "B" reports VIF and tolerance level after dropping variables with high VIF scores.

	VIF	Tolerance
Panel A: Initial set of Explanatory Variables		
Size Measure (Logassets)	1.210	0.829
Market Beta	1.050	0.953
Coverage Measure 1	4.430	0.226
Coverage Measure 2	3.740	0.267
Leverage Measure 1	7.460	0.134
Leverage Measure 2	7.330	0.136
Profitability Measure 1	1.250	0.802
Profitability Measure 3	1.440	0.696
G-Score	1.070	0.934
% Institutional Investment	1.120	0.891
% of Outside Directors	1.350	0.742
Mean VIF	2.860	
Panel B: Final set of Explanatory Variables		
Size Measure (Logassets)	1.150	0.867
Market Beta	1.040	0.963
Coverage Measure 1	1.630	0.614
Leverage Measure 1	1.460	0.684
Profitability Measure 3	1.260	0.792
G-Score	1.070	0.936
% Institutional Investment	1.110	0.902
% of Outside Directors	1.340	0.747
Mean VIF	1.260	

Model 1-Based on Financial Information Only

We begin our analysis evaluating only the impact of financial variables in model one. The ordered probit estimation method used is explained in section 3.3.2, and is based on standard maximum likelihood techniques. The ordered probit model explained by equation (3.2) assumes that the linking variable $Y_{it,}$ which is the censored data from order 0 through 3, is a linear function of the explanatory variables. The highest order 3 is assigned to the highest credit ratings and 0 to the lowest credit ratings in our sample. Utilising a linear relationship to associate $Y_{it,}$ with the explanatory variables would be implausible when the explanatory variables are skewed. We explained in our methodology section the truncation of our coverage measure to eliminate skewness. Based on the method used to convert our credit ratings into ordered numbers, a positive sign on the variables would indicate a predicted improvement in credit ratings and the negative sign signifies deterioration in credit quality.

Table 3.7 presents results for our financial information-based ordered probit model. Panel A of table 3.7 reports the results based on S&P ordered credit ratings, and panel B reports the results based on Moody's ordered credit ratings. For both the rating agencies, we observe positive signs on the coefficients of our size measure (log of total assets), coverage measure (EBITDA to interest charge) and profitability measure (OIADB to sales). The predicted signs for these three variables are also positive: as greater size, better coverage ratios and higher profitability all appear to contribute towards likelihood of high credit ratings. We also observe that for both the rating agencies, we have negative coefficients on both market beta and leverage variables. This suggests that an increase in beta value and leverage in a firm increases the likelihood of having a lower credit rating. We find in both panels A and B that all variables are highly statistically significant, showing the relevance of each variable to ordered credit ratings.

We observe from the last column of table 3.7 on both panel A and B that change in one standard deviation in the size measure has the greatest impact on improvement and deterioration of credit quality for both the rating agencies. This can also be seen from the high Z statistic associated with the coefficient. Comparing the two CRAs, we observe conformity in case of size variable having the greatest effect on the change in credit ratings. However, we observe some differences in the importance of one standard deviation shocks to the change in overall credit ratings. Panel A last column suggests that market beta has the second highest effect on the S&P credit ratings, but we observe that coverage plays a more important role in Moody's case. The least effective variable in case of S&P is our profitability measure, but we observe that leverage is the least important in the case of Moody's. This is preliminary evidence of differences in the importance of selected variables across agencies in assigning ratings.

Table 3.7 Model 1-Financial Variables Only

The Estimates are for the ordered probit model parameters using a panel data sample of observations from 1995-2009. The beta coefficient estimates are for the independent variables in the linear part of the model. The model is based on only financial variables. The Lower boundaries for rating category parameters are the estimates of the partition parameters for the rating categories. The panel data is of firms over fifteen years from 1995 through 2009 ranging in number from a low of 212 in 1995 to a high of 460 in 2009.

	Coefficient	Standard Error	Z Statistic	P-value	Coefficient * Variable Std. dev.
Panel A: Ordered probit model output for S&P					
Size Measure (Log assets)	0.462	0.014	32.71	0.000	0.576
Market Beta	-0.682	0.033	-20.81	0.000	-0.363
Coverage Measure	0.027	0.002	14.73	0.000	0.311
Leverage Measure	-1.884	0.144	-13.06	0.000	-0.274
Profitability Measure	3.375	0.283	11.93	0.000	0.260
BBB	2.443	0.135			
A	3.858	0.139			
AA/AAA	5.375	0.149			
Log Likelihood	-5035.19				
LR χ^2	3152.68			0.000	
Pseudo R^2	0.238				
Panel B: Ordered probit model output for Moody's					
Size Measure (Log assets)	0.488	0.014	34.13	0.000	0.609
Market Beta	-0.604	0.033	-18.37	0.000	-0.321
Coverage Measure	0.030	0.002	16.45	0.000	0.351
Leverage Measure	-1.613	0.145	-11.12	0.000	-0.234
Profitability Measure	3.470	0.286	12.15	0.000	0.267
Baa	2.996	0.137			
A	4.369	0.142			
Aa/Aaa	5.941	0.153			
Log Likelihood	-4935.61				
LR χ^2	3194.72			0.000	
Pseudo R^2	0.245				

Note: In our model one, we only use variables based on financial information of the firm. Financial variables included are based on firm's financial information: These include coverage measure-earnings before interest (EBITDA) to interest charge, leverage measure-long-term debt(DLTT) to total assets (TA), profitability measure - net income to total assets, and size measure-log of assets. Market beta is based on beta value of firm movement compared to NASDAQ/NYSE.

As explained in our methodology section 3.3.2, as a goodness-of-fit model we use predicted ratings from our estimated model and compare these predicted ratings with the actual ratings. Table 3.8 reports the matrix of actual ratings versus predicted ratings. Panel A reports the results for S&P, and panel B reports for Moody's. Based on financial information only, our model correctly predicts 53.93% of S&P credit ratings, and 55.01% of Moody's credit ratings. In our sample, we observe that

Moody’s has lower average credit ratings than S&P. Our ordered probit model predicts Moody’s credit ratings to be slightly better than S&P. In both the rating agencies, our model is more successful in the two lower rating categories BB/B and BBB. The model is least successful in the highest rating category of AA/AAA. The model correctly predicts only 24.17% in case of S&P and 28.23% in case of Moody’s.

Table 3.8 Model 1-Prediction Accuracy

This prediction success matrix compares the predictions of our estimated ordered model with actual S&P and Moody's ratings. This prediction matrix is based on ordered probit model using financial information only, which is our model one in the study. This measure of goodness of fit is estimated based on a panel data sample of 5192 observations from the year 1995 to 2009. This matrix shows, for instance, that the panel “A” contains total 393 AAA rated firms. The predicted ratings for these actual AAA ratings are: AAA/AA for 95, A for 238, BBB for 60 and BB/B for 0. Similarly, panel B presents results for our Moody’s ratings.

Predicted Rating	Actual Rating				Total Predicted	% Correct Prediction
	BB/B	BBB	A	AAA/AA		
	Panel A: Predictions Based on S&P Rating (Financial Only)					
BB/B	881	308	31	0	1220	61.01%
BBB	523	1247	708	62	2540	64.28%
A	40	379	577	236	1232	40.78%
AAA/AA	0	6	99	95	200	24.17%
Total Actual	1444	1940	1415	393	5192	53.93%
	Panel B: Predictions Based on Moody's Rating (Financial Only)					
Ba/B	1073	393	37	8	1511	66.19%
Baa	508	1109	672	42	2331	59.02%
A	40	370	580	189	1179	42.68%
Aaa/Aa	0	7	70	94	171	28.23%
Total Actual	1621	1879	1359	333	5192	55.01%

There may be several reasons explaining why the ratings of lower rated firms are more correctly predicted by our model as compared to the two higher ratings categories. Possible reasons are that out of 5192 observations, only 393 (7.57%) from S&P and 333 (6.41%) from Moody’s are actually placed in the highest rating category. In our settings of maximum likelihood, it may be that our likelihood function is maximised by assigning very few observations to the top category. Another reason is that the fundamentals between a firm rated A and firm in AA/AAA category are not significantly different. Finally, following Blume et al. (1998) it is possible that other omitted variables that are not part of the model, such as management quality, may determine the difference between two highest rating categories.

Model 2-Based on Governance and Financial Variables

In our model 2, we continue to use our initial financial variables as controls, and add three additional governance-related variables. Table 3.8 reports the results for this model. They reveal that we observe the same signs for both the CRAs with respect to all three governance variables. We find all the variables to be significant at 1% level, the only exception is the percentage of institutional investment in panel A being significant at 5% level. The results all allocate a positive sign to G-Score, suggesting that the higher the management controls, the higher the credit ratings obtained from the two agencies. This result is consistent with the findings of Ashbough et al. (2006), who also find positive and significant coefficient on the G-Score. Though, this is against the predicted signs, as one may expect higher shareholder rights to ensure better corporate governance and more effective controls on management activity resulting in improved firm performance[59]. Gompers et al. (2003) find that firms with lower G-Score have higher firm value, higher profits, higher sales growth, and lower capital expenditures. These factors may work towards improvement in credit quality; however our results suggest both the rating agencies give higher ratings to firms having higher G-Score.

We also find a positive sign on our other two governance variables, the percentage of institutional investment and the percentage of board independence. According to Standard and Poor's (2002), their governance framework focuses on four related components, namely: ownership structure and influence, financial transparency, financial stakeholders rights and relations, and board structure and processes. Previous literature, for instance Ashbough et al. (2006) has associated the G-Score measure with financial stakeholder's rights and relations, the percentage of board independence measure with board structure and processes, and the percentage of institutional investment measure with ownership structure and influence. The positive sign for both the agencies indicates that the greater the degree of board

[59] Gompers et al. (2003) using a sample of 1500 firms during 1990's find that taking a long position in firms with the strongest shareholder rights and a short position in firms with the weakest shareholder rights yields an average abnormal return of 8.5% per year.

independence, the higher the chances of obtaining a higher credit rating. Similarly, the higher the percentage of institutional investment, the higher the chances of receiving a higher credit ratings. These results are consistent with the findings of Bhojraj and Sengupta (2003), who hypothesise that firms with a greater proportion of outside directors on the board provide better monitoring of management actions, thereby protecting all stakeholders' rights. This is taken a positive signal by the rating agencies, and higher credit ratings are assigned to these firms. Similarly, the results on the percentage of institutional investment are also consistent with the findings of both Bhojraj and Sengupta (2003) and Ashbough et al. (2006), who explain that higher institutional investment signifies stronger confidence and active monitoring.

Table 3.9 suggests the relationship of all the governance variables with the credit ratings for both the CRAs is strongly significant. If we look at the final column of table 3.9, that is the product of the estimated coefficient and the individual standard deviation, we again find some differences in economic significance of these variables between the two rating agencies. Panel A suggests that none of the three governance related variables play a very significant role in determining S&P's credit ratings. Indeed, ranking the significance of each variable in order, we find that all three governance related are amongst the lowest three in determining credit ratings. Similarly in the case of Moody's, we find that a change of one standard deviation in the case of the G-Score and the percentage of institutional investment variables play the least significant role in determining credit ratings. However, the percentage of outside directors plays an important role for Moody's ratings allocation, as it lies third in the ranking in terms of its impact. This may suggest Moody's assigns more importance to the board structure compared to S&P in the determination of higher credit ratings.

In table 3.10, we present a prediction comparison matrix. Panel A reports the prediction success matrix for S&P, whereas panel B reports the results for Moody's. We find that overall, our financial and governance variables are able to predict 55.59% in case of S&P, and 57.74% in case of Moody's. Comparing our table 11 matrix with the table 10 matrix, we find an overall improvement of 1.66% in case of S&P, and 2.73% in Moody's correct predictions. These results suggest that based on

Table 3.9 Model 2-Financial and Governance Variables

The Estimates are for the ordered probit model parameters using a panel data sample of 4608 observations from 1995-2009 based on S&P ratings. The beta coefficient estimates are for the independent variables in the linear part of the model. The model is based on only financial, governance, industry and other variables The Lower boundaries for rating category parameters are the estimates of the partition parameters for the rating categories. The panel data is of firms over fifteen years from 1995 through 2009 ranging in number from a low of 203 in 1995 to a high of 384 in 2009.

	Coefficient	Standard Error	Z Statistic	P-value	Coefficient * Variable Std. dev.
Panel A: Ordered probit model output for S&P ratings					
Size Measure (Log assets)	0.42	0.01	28.67	0.000	0.527
Market Beta	-0.67	0.03	-20.14	0.000	-0.357
Coverage Measure	0.03	0.00	15.23	0.000	0.327
Leverage Measure	-1.69	0.15	-11.41	0.000	-0.246
Profitability Measure	3.32	0.29	11.56	0.000	0.256
G-Score	0.07	0.01	10.97	0.000	0.184
% Institutional Investment	0.23	0.10	2.26	0.024	0.038
% of Outside Directors	1.22	0.11	11.57	0.000	0.219
BBB	3.82	0.163			
A	5.31	0.169			
AA/AAA	6.87	0.179			
Log Likelihood	-4853.00				
LR χ^2	3517.07			0.000	
Pseudo R^2	0.266				
Panel B: Ordered probit model output for Moody's ratings					
Size Measure (Log assets)	0.430	0.015	28.89	0.000	0.537
Market Beta	-0.590	0.034	-17.58	0.000	-0.314
Coverage Measure	0.032	0.002	16.81	0.000	0.366
Leverage Measure	-1.373	0.151	-9.11	0.000	-0.199
Profitability Measure	3.357	0.291	11.55	0.000	0.259
G-Score	0.049	0.006	7.52	0.000	0.127
% Institutional Investment	0.342	0.102	3.37	0.001	0.057
% of Outside Directors	1.860	0.109	17.09	0.000	0.334
Baa	4.526	0.168			
A	6.006	0.175			
Aa/Aaa	7.662	0.187			
Log Likelihood	-4683.56				
LR χ^2	3698.82			0.000	
Pseudo R^2	0.283				

Note: In our model two, we use financial and governance variables. Financial variables included are based on firm's financial information: These include coverage measure-earnings before interest (EBITDA) to interest charge, leverage measure-long-term debt(DLTT) to total assets (TA), profitability measure - net income to total assets, and size measure-log of assets. Market beta is based on beta value of firm movement compared to NASDAQ/NYSE. We use three governance related variables, G-Score based on Gompers et al.(2003), percentage of Institutional Investment in firm's common stock, and percentage of firm's outside directors on board.

Table 3.10 Model 2-Prediction Accuracy

This prediction success matrix compares the predictions of our estimated ordered model with actual S&P and Moody's ratings. This prediction matrix is based on ordered probit model using financial information and our selected governance variables, which is our model two in the study. This measure of goodness of fit is estimated based on a panel data sample of 5192 observations from the year 1995 to 2009. This matrix shows, for instance, that the panel "A" contains total 393 AAA rated firms. The predicted ratings for these actual AAA ratings are: AAA/AA for 110, A for 228, BBB for 44 and BB/B for 0. Similarly, panel B presents results for our Moody's ratings.

Predicted Rating	Actual Rating				Total Predicted	% Correct Prediction
	BB/B	BBB	A	AAA/AA		
Panel A: Predictions Based on S&P Rating (Financial and Governance)						
BB/B	910	315	27	0	1252	63.02%
BBB	496	1228	652	51	2427	63.30%
A	38	389	647	241	1315	45.72%
AAA/AA	0	8	89	101	198	25.70%
	1444	1940	1415	393	5192	55.59%
Panel B: Predictions Based on Moody's Rating (Financial and Governance)						
Ba/B	1093	365	25	2	1485	67.43%
Baa	506	1154	605	34	2299	61.42%
A	22	357	656	202	1237	48.27%
Aaa/Aa	0	3	73	95	171	28.53%
	1621	1879	1359	333	5192	57.74%

our set of variables, adding three governance related variables improves the prediction of Moody's marginally more than S&P's. While, the increase in predictive power is fairly small in percentage terms, if we look at the rating categories, we see a more pronounced improvement in the predictions associated with the "A" category firms in both the agencies. This improvement in correct predictions in a rating category "A" is close to 5% for both rating agencies. Similarly, we find a slight improvement in rating predictions across other categories as well. We also report the model log likelihood and pseudo R^2, we find subsequent higher (lower in absolute terms) log likelihood for model two compared to model one. Similarly, we observe our pseudo R^2 also improves for both the agencies in our model two.

Model 3-Based on Governance, Financial and other Variables

In table 3.11 we report results of our final model 3. This model uses financial, governance and three other additional variables to explain assigned credit ratings.

We incorporate two dummy variables, one linking a firm's rating shopping behaviour, and the other capturing any change in rating allocation after the introduction of regulation FD. Just to recall, regulation FD, implemented by SEC on October 23, 2000, prohibits U.S. public companies from making selective, non-public disclosures to favoured investment professionals. The regulation provides a conditional exception for information disclosed to rating agencies, provided that the information is used solely to prepare a credit rating. Our final additional variable is the use of the GDP rate as a proxy to capture the state of the economy or business cycle. Any economic significance and improvement in overall rating predictions by adding these variables would demonstrate the importance of certain behavioural aspects in the assignment of credit ratings.

Our model 3 results shown in table 3.11 shows the signs and economic significance of our three additional variables. The two agencies exhibit the same signs for all the variables. We find a negative sign on the rating shopping variable for both the agencies. The negative sign indicates that for the same set of fundamentals, a firm's assigned a lower rating if it has more than three credit ratings. This indicates that the two rating agencies are more focused towards reputation concerns. Criticism has also been directed at the rating agencies in terms of conflict of interest. These reputation concerns may force the CRAs to have more stringent standards towards firms that exhibit rating shopping behaviour. Covitz and Harrison (2003) also provide evidence of reputation concerns by generating testable predictions regarding the anticipation of credit-rating downgrades by the bond market. Their findings strongly indicate that the rating changes do not appear to be influenced by the inherent conflicts of interest, but rather, suggest that rating agencies are motivated primarily by reputation-related incentives. One criticism directed at the rating agencies is that firms engage in rating shopping in an effort to secure favourable credit ratings. In terms of S&P and Moody's, we conclude that firms having three ratings face more stringent standards.

Table 3.11 Model 3-Financial, Governance and Other Variables

The Estimates are for the ordered probit model parameters using a panel data sample of 4608 observations from 1995-2009 based on S&P ratings. The beta coefficient estimates are for the independent variables in the linear part of the model. The model is based on only financial, governance, industry and other variables The Lower boundaries for rating category parameters are the estimates of the partition parameters for the rating categories. The panel data is of firms over fifteen years from 1995 through 2009 ranging in number from a low of 203 in 1995 to a high of 384 in 2009.

	Coefficient	Standard Error	Z Statistic	P-value	Coefficient * Variable Std. dev.
Panel A: Ordered probit model output for S&P ratings					
Size Measure (Log assets)	0.508	0.017	29.86	0.000	0.635
Market Beta	-0.512	0.035	-14.83	0.000	-0.272
Coverage Measure	0.032	0.002	16.88	0.000	0.374
Leverage Measure	-1.502	0.153	-9.83	0.000	-0.218
Profitability Measure	3.231	0.296	10.92	0.000	0.249
G-Score	0.071	0.007	10.76	0.000	0.185
% Institutional Investment	0.972	0.107	9.08	0.000	0.163
% of Outside Directors	1.754	0.110	15.94	0.000	0.315
Rshop	-0.112	0.037	-3.00	0.003	
Bcycle	0.045	0.010	4.63	0.000	
RegFD	-0.943	0.042	-22.41	0.000	
BBB	5.032	0.185			
A	6.685	0.193			
AA/AAA	8.421	0.205			
Log Likelihood	-4478.90				
LR χ^2	4265.26			0.000	
Pseudo R^2	0.323				
Panel B: Ordered probit model output for Moody's ratings					
Size Measure (Log assets)	0.551	0.018	31.45	0.000	0.689
Market Beta	-0.410	0.035	-11.69	0.000	-0.218
Coverage Measure	0.037	0.002	18.77	0.000	0.425
Leverage Measure	-1.062	0.156	-6.79	0.000	-0.154
Profitability Measure	3.381	0.303	11.16	0.000	0.261
G-Score	0.050	0.007	7.46	0.000	0.131
% Institutional Investment	1.212	0.109	11.08	0.000	0.203
% of Outside Directors	2.582	0.116	22.30	0.000	0.464
Rshop	-0.210	0.038	-5.51	0.000	
Bcycle	0.060	0.010	6.10	0.000	
RegFD	-1.057	0.043	-24.37	0.000	
Baa	6.218	0.195			
A	7.907	0.205			
Aa/Aaa	9.799	0.221			
Log Likelihood	-4217.98				
LR χ^2	4629.97			0.000	
Pseudo R^2	0.354				

Note: In our model three, we use financial, governance and conflict of interest variables. Financial variables computed are based on firm's financial information: These include coverage measure-earnings before interest (EBITDA) to interest charge, leverage measure-long-term debt(DLTT) to total assets (TA), profitability measure - net income to total assets, and size measure-log of assets. Market beta is based on beta value of firm movement compared to NASDAQ/NYSE. We use three governance related variables, G-Score based on Gompers et al.(2003), percentage of Institutional Investment in firm's common stock, and percentage of firm's outside directors on board. Other variables are dummies to be used as proxies for selected criticism on credit ratings: Rshop is a 0,1 dummy for firms with three or more ratings to show rating shopping behaviour. Bcycle is a 0,1 dummy for two recession periods in our sample year 2001 and 2008-09. RegFD is a 0,1 dummy for period showing pre regulation fair disclosure (1995-2000) and post regulation fair disclosure (2001-2009). We also use industrial dummies to classify our observations on GICS sector allocation

We find a highly significant negative sign on the Regulation FD dummy, suggesting that if a firm has higher credit rating in the pre-regulation period, there is a greater probability that an equivalent firm (with the same fundamentals) will receive a lower credit rating in the post regulation period. Regulation FD limits non-public information disclosure to favoured investment professionals, but allows CRAs from access to non-public information. This regulation has further enhanced the importance of credit ratings in the capital markets, as the usage and reliance upon credit rating agency information has increased. Jorion et al. (2005) also examine the impact of Regulation FD, and find that the informational effect of downgrades and upgrades is much greater in the post-FD period. Another interpretation, consistent with Blume et al. (1998), of this negative sign on the dummy variable is that over our data period window, rating agencies have become more stringent in their standards for the award of higher ratings, year by year. They report that S&P's standards are becoming stringent by adding year dummies in their sample. We provide evidence that this finding is not limited to S&P standards only, but Moody's also evidence stringent standards during our post Regulation FD period.

Our last set of additional variables relate to the business cycle. We use the U.S. GDP growth rate as a proxy for the stage of the current business cycle. A higher GDP growth rate signifies higher economic growth, and lower/negative economic growth signifies a slowdown in economy (or possible recession). In both the agencies, we find a positive and statistically significant sign on business cycle. This shows that during periods of high economic growth a firm exhibiting similar firm characteristics tends to obtain a higher credit rating. During low growth periods we observe that CRAs reduce credit ratings. One explanation of this finding relies on reputational concerns. Our data window of 1995 through 2009 encompasses both recession and boom period. During our data window, we observe a recession of eight months in the year 2001 when we observe the dot.com bubble crash and in the years 2007-08 there are eighteen months when US economy experienced the effects of the financial crisis[60].

The negative sign on the business cycle suggests CRAs are indeed more stringent during economic downturns. From investor's point of view and from rating agencies stated policy of forward looking approach this is a concern. Credit ratings are intended to signify future outlook for an issuer. As such, it may be argued that business cycles may not play a significant role in credit rating assignments. As both the agencies follow credit analyst based approaches in the rating process, a general criticism of the subjective element involved in the rating process is consistent with our empirical results. These findings may be interpreted as contradicting rating agencies forward-looking approach, as they state that their analysts already take into consideration any business cycle and changes in the economic environment when assigning a rating. These findings of a potential business cycle effect also contradict the findings in Amato and Furfine (2004) who detect no evidence of rating agencies sensitivity towards business cycle. However, they also document evidence of procyclicality in their sub-samples of investment-grade firms only, and in newly assigned ratings as used as a dependent variable. Since, we exclude lower rated firms (due to low frequency in each category) from our sample, and we only have one rating category below investment grade, our findings of procyclicality in rating agency behaviour can be as reconciled with their evidence of procyclicality in investment grades rating allocation.

Blume et al. (1998) uses a comparison of the most probable ratings to the actual ratings can be used to assess the goodness-of-fit of a probit model. To observe the goodness-of-fit of our model[61], we utilise a prediction success matrix which is shown in table 3.12, where panel A reports S&P, and panel B reports Moody's comparison of correct and predicted credit ratings matrix. We find that with a comprehensive set of variables, we are able to correctly predict 61% of S&P and 63% of Moody's

[60] Refer to National Bureau of Economic research (NBER) period of recessions.

[61] To observe the impact of these variables, we do not estimate the product of coefficient and individual standard deviation, as we use the dummies and one GDP figure for each year.

ratings. Comparing the two rating agencies, based on our given data overall, we slightly more able to better predict Moody's credit ratings. Here it may be pertinent to note once again that overall in our data sample, Moody's has lower ratings as compared to S&P.

Table 3.12 Model 3-Prediction Accuracy

This prediction success matrix compares the predictions of our estimated ordered model with actual S&P and Moody's ratings. This prediction matrix is based on ordered probit model using financial information, governance variables and our selected conflict of interest variables, which is our model three in the study. This measure of goodness of fit is estimated based on a panel data sample of 5192 observations from the year 1995 to 2009. This matrix shows, for instance, that the panel "A" contains total 393 AAA rated firms. The predicted ratings for these actual AAA ratings are: AAA/AA for 119, A for 248, BBB for 26 and BB/B for 0. Similarly, panel B presents results for our Moody's ratings.

Predicted Rating	Actual Rating				Total Predicted	% Correct Prediction
	BB/B	BBB	A	AAA/AA		
	Panel A: Predictions based on S&P rating (Full Model)					
BB/B	983	318	28	0	1329	68.07%
BBB	442	1247	496	22	2207	64.28%
A	19	371	815	251	1456	57.60%
AAA/AA	0	4	76	120	200	30.53%
	1444	1940	1415	393	5192	60.96%
	Panel B: Predictions based on Moody's rating (Full Model)					
Ba/B	1148	376	16	2	1542	70.82%
Baa	456	1177	450	13	2096	62.64%
A	17	324	822	210	1373	60.49%
Aaa/Aa	0	2	71	108	181	32.43%
	1621	1879	1359	333	5192	62.69%

To elaborate, we further examine panel A of table 3.12. Here we find that the lowest category in our sample is the best predicted and highest is the least correctly predicted. In the case of Moody's, almost 71% of the lowest category Ba/B is correctly predicted. If we compare panel A and panel B, we find that Moody's has a higher percentage of correct predictions in three of the four categories, and it is only in the BBB category that S&P has a higher percentage of correct predictions.

If we compare our prediction matrix in table 3.12 with the previous prediction matrices reported in table 3.8 and 3.10. We find that in terms of goodness-of-fit, our final model is the best model for predicting credit ratings. In both the agencies, we are able to predict over 60% of our ratings. An important finding is that in addition to financial variables, adding the three additional controls adds more explanatory power to our model than adding the three governance variables. Another important finding is that there is a significant improvement in correct predictions in the higher rating categories from adding additional variables. We find that our model is able to correctly predict 58% of S&P's ratings and 60.49% of Moody's in the "A" rating category, compared to 45.72% and 48.27% before adding the variables. This is an improvement of 26.85% in "A" category of S&P's, and 25.31% in Moody's. We also find improvement in our highest rating category of "AAA", as we are now able to predict 31% of S&P's and 32% of Moody's ratings. If we compare these two numbers with the financial only model, we find an increase of 5% (or above) in case of S&P and 4% in case of Moody's. We observe that in two lower categories, we observe 5% increase in overall prediction in S&P's "BB/B" category from previous model, and 3% increase in Moody's case.

Looking at other goodness-of-fit measures, we find similar results. In S&P, the log likelihood for our model three is -4478.90 is higher than the other two -4853.00 in model two and -5035 in model three. Similarly, for Moody's the log-likelihood for model three is -4217 compared to -4683.56 of model 2 and -4935 of model one. We observe similar improvements in our pseudo R^2 for our model three using all the selected variables.

3.4.3 Further Discussion and Robustness

In accordance with the previous literature on rating information, we utilise four aspects of financial characteristics in our model. These include firm size, leverage, coverage and profitability. The previous literature has used a number of financial ratios and related information to determine the same four aspects of firm's financial health. Following same procedure, as mentioned in our methodology section, we estimate several financial ratios to determine these four characteristics of a firm. In order to avoid potential multicollinearity, we only include one ratio each as mentioned in our empirical results and methodology sections. However, if we replace our different financial ratios, our model predictive power is unchanged. For instance, we report results based on coverage measure namely EBITDA to interest charge, but overall model prediction remains same if we use OIADP to interest charge. We test these for our other ratios for firm leverage and profitability too, and our results are unchanged.

We also estimate our final model by using a dummy variable to indicate the stages of the business cycle. Based on NBER dates, we use a (0, 1) dummy variable to characterise the two recession periods in our data window. These dummy variables are also used by Amato and Furfine (2004) to measure the state of the economy, with a dummy 1 denoting a recession period and 0 signifying other periods. As such, periods incorporate a dummy for recession, namely the years 2001 and both of 2007 and 2008. In line with our findings using the GDP growth rate as a proxy for our business cycle, we find a similar significant negative sign on our recession dummy, corroborating previous findings.

This study analyses panel data using maximum likelihood estimation methods. Previous literature on the attribution of different factors to determine credit ratings has generally agreed on the use of ordered probit model. Similarly, the use of panel data also raises questions of whether random/fixed effects are catered for. To the best of our knowledge, no study has previously used random effects ordered probit model in the corporate credit ratings settings, although we find studies of sovereign credit ratings which use random effects ordered probit models. These studies use a random effects ordered probit model, as such a specification enables them to consider the existence of an additional, normally distributed, country specific error. Generally, two methods are utilised to determine the best model in the literature. First, the prediction capability of the model and second, the statistical significance of the variables. Alsakka and Gwilym (2010) use likelihood ratio (LR) statistics, with one degree of freedom, to compare the results from an ordered probit model and random effects probit model to select the preferred model. The random effects model is generally perceived to be computationally more intense and time consuming. In sovereign credit ratings, for instance, it is considered the best approach, as it considers cross-country geo-political differences, political risk and social tensions (Trevino and Thomas (2001), Bissoondoyal-Bhhnick (2005)). All these factors are considered to play an important role in the sovereign credit ratings settings.

We also estimate our final model with all the variables employing a random effects ordered probit model [62].We consider company specific errors as an additional normally distributed error term. We use two methods to determine the model generating best-fit. First, our conclusion is based on the comparison of the significance of our variables, and second we compare McFadden's pseudo R^2.

Table 3.13 reports the outcome of our estimated random effects ordered probit model for both the agencies. Panel "A" reports the estimation outcome for S&P. We observe that two variables, profitability and rating shopping, are not statistically significant. Comparing the two pseudo R^2, we see that the pseudo R^2 for the random effects model is 0.235, compared to the 0.323 obtained from the standard ordered probit model used in our empirical results. Similarly, in panel "B", we observe that in Moody's case the rating shopping variable is also statistically significant. The Pseudo R^2 is also lower than that from our full model, estimated in table 3.9.

We conclude that this indicates that although we obtain the same signs on the estimated variables, overall our data is better explained through utilising an ordinary ordered probit model. This satisfies our findings and conclusions based on the available data.

[62] Estimation of the random effects ordered probit model is performed by applying the "reoprob" user-contributed command, which was introduced to STATA software by Frechette(2001a,b).

Table 3.13 Random Effects-Ordered Probit Model

The Estimates are for the random effects ordered probit model parameters using a panel data sample of 5192 observations from 1995-2009 based on S&P's and Moody's credit ratings. The beta coefficient estimates are for the independent variables in the linear part of the model. The model is based on only financial, governance, and other variables The Lower boundaries for rating category parameters are the estimates of the partition parameters for the rating categories. The panel data is of firms over fifteen years from 1995 through 2009 ranging in number from a low of 212 in 1995 to a high of 460 in 2009.

	Coefficient	Standard Error	Z Statistic	P-value
Panel A: Random Effects Ordered Probit Model Output for S&P Ratings(Pseudo R^2=0.235)				
Size Measure (Log assets)	0.789	0.037	21.21	0.000
Market Beta	-0.467	0.056	-8.39	0.000
Coverage Measure	0.044	0.003	13.53	0.000
Leverage Measure	-3.436	0.272	-12.63	0.000
Profitability Measure	0.457	0.282	1.62	0.105
G-Score	0.099	0.014	6.88	0.000
% Institutional Investment	1.301	0.175	7.45	0.000
% of Outside Directors	1.900	0.222	8.56	0.000
Rshop	-0.197	0.122	-1.61	0.108
Bcycle	0.089	0.013	6.63	0.000
RegFD	-1.462	0.066	-22.14	0.000
BBB	6.841	0.380	18.000	0.000
A	10.220	0.413	24.740	0.000
AA/AAA	13.998	0.434	32.290	0.000
Panel B: Random Effects Ordered Probit Model Output for Moody's Ratings(PseudoR^2=0.256)				
Size Measure (Log assets)	0.802	0.042	19.05	0.000
Market Beta	-0.291	0.059	-4.94	0.000
Coverage Measure	0.037	0.004	9.40	0.000
Leverage Measure	-3.254	0.290	-11.23	0.000
Profitability Measure	1.193	0.337	3.54	0.000
G-Score	0.053	0.015	3.63	0.000
% Institutional Investment	2.181	0.192	11.34	0.000
% of Outside Directors	3.765	0.215	17.53	0.000
Rshop	0.149	0.139	1.08	0.282
Bcycle	0.132	0.014	9.12	0.000
RegFD	-1.621	0.070	-23.30	0.000
Baa	8.791	0.438	20.06	0.000
A	12.416	0.466	26.66	0.000
Aa/Aaa	16.256	0.500	32.49	0.000

Note: In our model three, we use financial, governance and conflict of interest variables. Financial variables computed are based on firm's financial information: These include coverage measure-earnings before interest (EBITDA) to interest charge, leverage measure-long-term debt(DLTT) to total assets (TA), profitability measure - net income to total assets, and size measure-log of assets. Market beta is based on beta value of firm movement compared to NASDAQ/NYSE. We use three governance related variables, G-Score based on Gompers et al.(2003), percentage of Institutional Investment in firm's common stock, and percentage of firm's outside directors on board. Other variables are dummies to be used as proxies for selected criticism on credit ratings: Rshop is a 0,1 dummy for firms with three or more ratings to show rating shopping behaviour. Bcycle is a US GDP growth percentage used as a proxy to demonstrate economic growth and business cycle. RegFD is a 0,1 dummy for period showing pre regulation fair disclosure (1995-2000) and post regulation fair disclosure (2001-2009).

3.5 Concluding Remarks

This study examines the importance of various financial and other variables in explaining the credit ratings issued by the two major rating agencies S&P and Moody's. We use index constituent issuer firms from S&P500, S&P 400 and S&P 600 indices which have received ratings from both the agencies. We examine 5192 firm-year observations from 1995 through 2009 utilising an ordered probit model. Based on ordered probit estimations, we also examine the prediction success matrix to determine the goodness-of-fit of the estimated model. We use three ordered probit model estimations to reach our conclusions. Our initial model is based on financial information only, and we subsequently add governance related variables and finally three additional variables to demonstrate the impact of potential criticism directed towards rating agencies. In all our models, our data explains Moody's credit ratings slightly better than S&P.

Our initial findings, based on our selected financial variables, suggest that the size measure has the most pronounced effect on the credit ratings for both the agencies. Interestingly, we also find certain difference in two rating agencies in terms of impact of these financial variables. Market beta has more effect on the credit ratings from S&P as compared to Moody's. The coverage ratio, which is also truncated in our study to reduce the skewness problems, has more importance in determining Moody's ratings than for S&P. In both the agencies, we find that changes in leverage and profitability play the least important role in the allocation of credit ratings. However, overall we conclude that all financial variables are highly significant factors in determining the assignment of credit ratings.

We also determine the effects of governance variables on firms' credit ratings by using a firm's initial financial characteristics as control variables. Specifically, we find that firm credit ratings are: (1) positively associated with a higher G-Score, indicating that firms with a greater degrees of management as opposed to shareholder control have higher credit ratings; (2) positively related to the percentage of institutional investment; and (3) positively related to overall board independence. In the case of S&P, changes in governance variables have the least impact of any variables on the allocation of credit ratings. With respect to Moody's, the percentage of board independence has a pronounced effect on predicting the allocation of credit ratings. By adding three governance variables, we find a slight improvement of around two percent in the predictive success of our model for both the agencies. This indicates that financial fundamentals are the primary source of information used in determining credit ratings.

Finally, we add three additional variables, which can be associated with the general criticisms directed towards rating agencies and also subjectivity elements involved in the rating process. Our final model findings suggest that the firms that have received at least three ratings face more stringent rating standards from the two agencies. We conclude that firms that exhibit rating shopping behaviour tend to get lower credit ratings as compared to other firms. This suggests the two major rating agencies may be concerned with their reputation. We also find that a variable capturing the introduction of Regulation FD has a highly significant negative impact, suggesting more stringent standards from the two agencies have arisen in the post-Regulation FD period. This has two aspects; first, after introduction of the Regulation FD, market participants may have placed an increasing reliance upon rating agencies information and ratings, which in turn has made the rating agencies more vigilant and stringent. Second, in line with Blume et al. (1998), rating standards appear to be becoming more stringent over time, and firms need to improve firm characteristics in order to maintain the same levels of ratings. The increase in the number of firms given low level ratings in our data is evidence that supports this hypothesis. We also find a positive and significant sign on our proxy for the stage of the business cycle. This suggests that rating agencies are more stringent during times of economic turmoil and slowdown.

An important finding of this study is that incorporating these three additional variables significantly improves our ability to predict firms allocated to the high rating category. This suggests that subjective element play an important role in discriminating between high rating category issuers, where incorporating only fundamentals fails to correctly predict higher rated firms.

Summarising our findings, we conclude that the two rating agencies differ in terms of the importance placed upon the variable. We do not find any significant differences in the signs of the variables across agencies, showing each variable has broadly the same impact on the assigned ratings. However, the importance placed upon each variable by each variable agency is different. In the next chapter we undertake further analysis to determine whether these preferential differences are the cause of the allocation of split credit ratings observed between the two agencies.

Chapter 4

Credit Rating Splits between Moody’s and S&P: Why do Split Ratings differ?

Summary

The study investigates the factors determining split credit ratings between S&P and Moody’s. This is the first study that investigates not only the likelihood of splits, but also the factors that contribute to determining why one agency has different ratings than the other. We use financial, governance and other factors that capture various subjective elements to explain split credit ratings. The study takes into account both splits at the notch and category level, and uses a two-stage Bivariate Probit estimation method. We use a sample of 5238 firm-year observations from S&P 500, S&P 400, and S&P 600 index constituent firms which have ratings from both Moody’s and S&P. We also investigate rating persistence in our sample. Our results suggest that the split ratings are persistent. Our findings at the notch level indicate that a firm having greater size, favourable coverage and higher profitability are less likely to have a split. However, smaller firms with unfavourable coverage and lower profitability are rated lower by Moody’s compared to S&P. In terms of governance related variables, S&P and Moody’s have congruent ratings for a firm having higher management control vis-à-vis shareholder rights. However, Moody’s places a higher value on board independence and allocates firms with higher board independence to high ratings than S&P, resulting in a split. Our findings suggest the business cycle does not play any significant role in deciding splits between the two agencies, but rating shopping and the introduction of regulation FD increase the likelihood of having splits. At the category level, we find that leverage level differences along with the other financial variables also play a role in explaining category level splits. However, neither the rating shopping behaviour nor the percentage of institutional investment plays any significant role in the likelihood of splits.

4.1 Introduction

Moody's and S&P dominate the global credit rating industry[63]. Both the major agencies have access to information that other investment houses and professionals do not have, with this access supported by relevant regulations[64]. Despite having access to such non-public albeit symmetric information, the two CRAs do not always agree on the assessment of credit quality. Approximately 20% of the US corporate bond issues have category or letter level[65] split ratings, and about 50% of sub-ratings or notch-level[66] ratings are splits (see for instance, Ederington (1986), Livingston and Jewell (1998)). Irrespective of the reasons behind split credit ratings, markets can react by treating these split rated issues as a separate credit quality. Cantor et al. (1997), Livingston and Jewell (1998) and Hseuh and Kidwell (1988) find bond yields on these split rated issues correspond to an average of the two split ratings. In a survey of the US and European fund managers, Cantor et al. (2007) finds 16% of the responding US fund managers use the higher of the two ratings, and 22% use the lower of the two ratings. Similarly, responding fund managers in the US also suggest only 9% of the respondents always use results from a specific agency while the others utilise results from any of the NRSRO ratings. This raises a question of whether there is self selection by the issuers in order to obtain a credit rating from an agency which they believe may be more favourably disposed to their situation.

Ederington (1986) does not find any consistent trends within split ratings, and concludes that split ratings are as a result of random errors. Morgan (2002) attributes split ratings to the impact of asset opacity, as financial firms having more opaque assets are more likely to have split ratings. Haggard et al. (2006) reveals lower quality financial reporting contributes to information uncertainty, which in turn creates uncertainty in the risk assessment, resulting in a split rating. However Livingstone et al. (2007) shows there is a degree of persistence in split ratings, as in

[63] Moody's and S&P have a combined market share of 80%. Together with Fitch, the number three agency by market share, they have over 95%. "Rating the rating agencies" The Economist, May 31st 2007.

[64] Regulation Fair Disclosure (FD), implemented on October 23, 2000, prohibits U.S. public companies from making selective, non-public disclosures to favoured investment professionals. This regulation has an exclusion enabling rating agencies to have access to non-public information.

[65] When AA is different from A and AAA, but not from AA+ and AA-.

[66] When AA is different from AA+ and AA-,

their sample about two thirds of initially split-rated bonds remain split-rated four years of rating transitions. This finding suggests credit splits are not caused by random errors, but there is a real difference of opinion by the agencies on the credit assessment of an issuer or an issue. Morgan (2002) finds that split ratings are lopsided, with Moody's consistently on the downside. However, at times S&P also rates lower compared to its counterpart Moody's in a split. It is important to understand the factors that determine the likelihood of a split, and why one agency places the same issuer in a higher or lower category compared to the other agency?

CRAs have attracted considerable attention due to the financial crisis of 2007-2008. The "issuer pay model" concerns both the regulators and investors, as it effectively damages the information intermediary role of a rating agency, and raises reputational concerns for the rating agencies. Despite having attracted considerable literature on the consequences of split ratings, little evidence is available on the determinants of credit rating splits. Issuers depending upon their financial profile may only seek a CRA where they expect to receive a higher credit rating. Similarly, investors making investment decisions using rating information may be better informed, if they know why one agency places the same issuer higher or lower? Plan sponsors and their fund managers include a variety of rating-based guidelines in the contractual arrangements; if they know the underlying factors contributing towards rating splits they may exhibit a preference for one agency over the other. Becker and Milbourn (2011) find evidence of rating inflation by Moody's and S&P in response to increased competition following the market entrance of the third largest rating agency, Fitch. This reinforces a need to further study the split credit ratings, and analyse differences of opinion in relation to the particular factors determining such ratings.

These differences of opinion are of two types. One difference is at a category level, and the other at a notch level. A category level difference may result in one agency placing as issuer in a category lower than investment grade threshold of BBB (Baa), and may deprive issuers of investment opportunities due to investment guidelines which allow investors to hold only investment grade issuers in their portfolio. Similarly, these differences raise questions of potential rating inflation creating problems from a regulatory perspective.

The study investigates split credit ratings between S&P and Moody's with the objective of discovering why one agency rates lower and other higher within a split rating? To determine the factors behind this phenomenon, we utilise firm level financial information as well as governance and other subjective elements shown to have explanatory power in the determination of credit ratings. Previous studies have shown that within splits, there is a consistent trend of "lopsided" behaviour, where Moody's is generally rating lower than S&P (see for instance, Morgan (2002) and Livingstone et al. (2007)). We study the factors potentially the underlying Moody's conservative stance on certain issuers and in other cases S&P's conservative stance within a split. In addition to the factors determining split credit ratings, we also study differences between splits at both the category level and at the notch level.

Following Livingstone et al. (2008) we first observe the persistence of splits in our sample. Subsequently we estimate two Bivariate Probit regressions to predict the likelihood of splits at the category and notch level. A Bivariate Probit model specification is more suitable in our setting, as in the first stage we observe the likelihood of splits, and in the second stage, why within a split, one agency rates lower than the other. Our explanatory variables include financial information based variables, governance related variables, and three additional variables used as proxies to account for possible subjectivity behind the allocation of split ratings. We utilise a sample of 5238 firm-year observations from S&P 500, S&P 400, and S&P 600 index constituent firms which have ratings from both the major agencies; S&P and Moody's. We estimate our bivariate probit regressions by considering notch level and category level splits as a dependent variable in the first model, and only category level splits as a dependent variable in the specification of the second model.

Our results confirm previous findings that split ratings are persistent, and over half the split rated firms remain splits even after fifteen years of rating transitions. Our findings at the notch level indicate that in terms of financial variables, a larger firm, and favourable coverage and profitability measures is less likely to have a split. However, smaller firms with unfavourable coverage and profitability measures is likely to be rated lower by Moody's as compared to S&P. In terms of governance related variables, S&P and Moody's both keep congruent ratings for firm having a higher degree of management control vis-à-vis shareholder rights. However, Moody's places a higher value on board independence and places firms with higher board independence in a high rating than S&P. Our other three variables suggest that the business cycle does not play any significant role in explaining splits between two agencies, although the rating shopping behaviour and the introduction of regulation FD increase the likelihood of having splits. The introduction of regulation FD has increased the likelihood of Moody's placing a firm lower in a split. In terms of category level splits, we find that leverage level differences along with other financial variables also play a role in explaining such category level splits. However, neither the rating shopping behaviour nor the percentage of institutional investment plays any significant role on the probability of having a split at the category level.

One key contribution to the literature on split credit ratings is that, we do not limit our analysis to the factors determining the likelihood of splits, but we further contribute by analyzing which factors determine one agency to have lower ratings than the other. Ederington (1986) concludes that the split ratings are caused by random errors. Morgan (2002) finds split ratings are due to asset opacity, and Livingstone et al. (2007) show there is a degree of persistence in split ratings. Morgan (2002) finds the split ratings are lopsided, with Moody's consistently on the downside. Our findings suggest that split ratings are caused by fundamental differences in relation to issuer credit profile, and we isolate those factors that determine the conservative and optimistic behaviour respectively of these two agencies. Second contribution is that we do not limit attention to only financial variables in explaining splits, but we include governance variables and other subjective elements to observe their impact on the likelihood of splits. We also contribute in terms of analyzing differences between notch level and category level splits.

The organization of the remainder of this chapter is as follows: Section 4.2 provides a literature review, Section 4.3 describes the sources and definitions of data utilised and also presents the bivariate probit model, Section 4.4 describes the empirical results and discusses the findings and the robustness of our results. Finally section 4.5 concludes.

4.2 Literature Review

The initial research on the credit rating industry focuses on the determinants of credit ratings. However, as the use of credit rating information increased, and the industry switched from a user pay model to an issuer pay[67] model, other research avenues opened up. One area that has attracted major research is the reasons behind split credit ratings. Split credit ratings occur when two or more CRAs differ on the assigned credit quality of an issuer or an issue. Split credit ratings convey additional information to the market, as bond yields and prices are set upon the perceived credit quality of the issuer. We observe that the research on split credit ratings has concentrated in two major directions. |The first studies the causes of split credit ratings, and the second branch studies the impact of split credit ratings on bond prices[68]. Our research is more focused towards the first branch of the literature, where we study the causes of differences of opinion between the two major CRAs S&P and Moody's. This section of the literature reviews the existing established hypothesis and econometric measures used in conducting research on the reasons underpinning split credit ratings.

Ederington (1986) is the first to explore possible reasons behind split credit ratings. Using a data sample of 493 new bond issues from 1975 through 1980, he uses an ordered probit model estimation using Mckelvey and Zavoina (1975) approach. The study revolves around three main hypotheses: 1. Do splits between Moody's and S&P signify difference in the risk standards of two agencies? 2. Does one agency tend to rate some issues higher than the other? 3. Do splits evidence the highly subjective nature of ratings? The selected sample has 13% split ratings. It is important to mention here that, during his sample period, only S&P was using the notch system. Hence, in split ratings notch level splits are not considered. The 13% figure of split ratings represents a difference at category level not at notch level, (for instance AA is different from A, but not from AA-). The results reveal that the ordered probit model explains Moody's credit ratings data better than S&P ratings.

[67] Fitch and Moody's started to charge corporate issuers for ratings in 1970, and S&P followed suit a few years later. This was mainly due to increase in the use of credit rating information after the 1970 recession during which many commercial papers issued by well-known issuers defaulted. This prompted market participants to actively seek credit ratings.

[68] See for instance Cantor et al. (1997), Jewell and Livingstone (1998) and Santos (2006).

The log likelihood is higher for the Moody's (lower in absolute terms), and the variance of the error term is higher for the S&P. The higher variance term leads to two important interpretations. One is that S&P is less consistent in rating industrial bonds, whereas another is that S&P uses additional information that is not included in the Ederington (1986) model. The first interpretation implies that S&P ratings are less useful. However, the second implies that S&P ratings are potentially more useful as they incorporate more than simply financial information. The study reports no evidence in the sample of a difference in standards, that one agency consistently sets higher division points between all ratings than does the other. Similarly, there is no evidence that they assign different weights to the major financial accounting measures. The conclusion reached is that the split ratings represent random differences of opinion on issues whose creditworthiness is close to the borderline between rating categories.

However, Livingston et al. (2008) argue that split rating are not completely caused by random errors. To address this issue it analyses the persistence in split credit ratings, by following the rating transitions of bonds which are split-rated at issuance. They use a sample period 1983[69] through 2000, and all the issues included in the sample have ratings from both S&P and Moody's. The results reveal that bond's with split ratings experience more rating changes as compared to those with non-split ratings. However, over 50% of the sample of split credit ratings remains split ratings even after four years of rating transitions. These findings suggest that the random differences hypothesis proposed by Ederington (1986) needs further research. If the two agencies maintain the relative creditworthiness of split ratings, even four years after initial issuance, this shows that splits arise not just because of random errors. In fact, this appears to indicate fundamental differences between the two agencies.

Moon and Stotsky (1993), using determinants extracted from the stated rating policy of S&P and Moody's as explanatory variables, study the causes of split credit ratings for municipal bonds. They use a cross-section of municipalities with a population of 25,000 people in the year 1981. They use a total of 892 municipality observations

[69] They start their sample from the year 1983 as Moody's introduced notch level credit ratings in the year 1982, while S&P started notch level credit ratings in the year 1974. By introducing notch level modifications, rating categories are further divided into plus and minus symbols in case of S&P and numbers 1 and 2 to Moody's.

with outstanding debt. Of these, 252 are rated by both the rating agencies, and 475 are rated only by Moody's, 4 are rated only by S&P, and 161 are not rated by either of the two agencies. Using a four-equation system, estimated by smooth simulated maximum likelihood techniques (SSMLE) [70] they construct minimum χ^2 tests on cross-equation restrictions based on optimal minimum distance estimations (ODME). The four equations are specified to incorporate quadvariate latent variables and covariates. The first equation is based on a city's propensity to obtain Moody's ratings, the second equation is Moody's perceived riskiness, the third equation is a city's propensity to obtain S&P's rating, and the last equation is S&P's perceived riskiness. These equations and correlation coefficients between different equations test various hypotheses. First, whether agencies weight the determinants of municipality ratings equal? Second, whether there is any issue of self selection related to a preference for one agency over the other by the market? Also, whether grouped rating classes (i.e. AAA, AA, etc.) represent the same risk classifications for Moody's and S&P's. (They test whether threshold coefficients are the same to a factor of proportionality). Their empirical results suggest self selection is only observed in Moody's, where they find municipalities with low Moody's ratings are less likely to obtain further Moody's ratings. On the contrary, the correlation coefficient between city's propensity to obtain S&P ratings and riskiness perceived by S&P ratings is insignificant. This suggests there is no self selection issue in the case of S&P, though their sample has a very low number of observations of S&P ratings and there may not be any systematic reason behind these findings. Empirical results suggest there are differences in rating determinants as well. They find rating determinants in S&P such as number of owner-occupied units, per capita income, the proportion of nonwhites population, per capita debt, the level of debt relative to income, southern and western region dummies, and largest municipality dummy variables to be insignificant, whereas these are significant in Moody's. They also find the thresholds for both Moody's and S&P's are different and strongly significant. They interpret this significance as the two rating agencies credit ratings representing different risk categories. The significance of rating determinants may

[70] The study adopts SSMLE proposed and applied by Borsch-Supan et al. (1990), and Hajivassiliou (1991).

well be due to the differences in sample size, as other similar studies on rating determinants do not show significant differences. Moreover, the study uses municipality credit ratings and its findings cannot easily be associated with corporate credit ratings, as studies related to corporate ratings do not find significant differences in rating determinants.

Cantor and Packer (1995) report that split credit ratings are more evident for junk bond[71] ratings than for investment grade bonds. They also report that, in general, Moody's and S&P ratings are congruent and spilt ratings are more visible when we compare the two big CRAs with smaller CRAs. They report that smaller rating agencies consistently rate higher on average than the two major agencies. For instance they report that the Duff and Phelps and Fitch ratings are between 1 and 1.5 rating notches higher than the ratings from Moody's and S&P. They argue that the split ratings between the big two and the other rating agencies signify differences in the rating scales for evaluating credit risk. However, they argue that rating splits are more apparent in cases where we compare two ratings using ratings for junk bonds, bank debt, and mortgage-backed securities. These smaller rating agencies assign a higher credit ratings compared to the big two rating agencies, and one ulterior motive behind obtaining a third rating in the case of junk bonds is that it may enable issuers to climb out of the junk category into the investment grade category. The study maintains that the two major rating agencies issue congruent ratings, whereas numerous other studies[72] report split credit ratings between the two major agencies. Secondly, Santos (2006) finds mid-quality bonds are highly likely to have a split rating and bonds with very high and very low credit quality have a lower likelihood of splits.

In another study, Cantor et al. (1997) use a cross-section of sample of 1137 corporate firms and compare credit ratings issued by the four CRAs in one year, 1993. They use the two major agencies, Moody's and S&P's rating, as mandatory agencies, and introduce two additional credit ratings by DCR[73] and Fitch[74] in order to compare

[71] Cantor and Packer (1995) classify a junk bond when Moody's or S&P rate an issue lower than BBB- level.

[72] Approximately 20% splits are reported at category level, and around 50% at notch level (see, for example, Jewell and Livingstone (1998) and Livingstone et al. (2007).

[73] Duff and Phelps Credit Rating Agency (DCR), which began rating a wide range of companies in 1982, has researched public utility firms since 1932.

rating differences between mandatory and optional agencies. Following Heckman's (1979) estimation method they employ a two-step approach to account for sample selection bias in the first stage and differences in rating standards in the second. The sample selection bias occurs when the additional CRAs are asked by issuers to rate issues, instead of relying upon unsolicited ratings from the two major rating agencies[75]. In the first stage they use probit regressions to estimate a firm's decision to have a third rating to demonstrate whether a firm exhibit any bias in selecting a third rating agency. They use different explanatory variables such as the location of a firm, the amount of time a firm is active in public debt, the amount of long-term debt, leverage ratios, coverage ratios, profitability ratios, weighted average ratings from S&P and Moody's, rating differences between Moody's and S&P, and marginally below investment grade ratings from Moody's and S&P. In the second stage, they use an ordered probit model to estimate differences in rating standards. The dependent variable represents three qualitative difference categories (higher, same, or lower) between mandatory and optional rating agencies. In the second stage they estimate three ordered probit models by using the constant and inverse Mills ratio obtained from the first stage probit regressions. The second model adds industry dummies while the third model also includes four additional financial variables; leverage, coverage, profitability, and the log of assets. The method helps them to investigate the following two hypotheses: H1: Sample selection bias does not cause the optional agency's average ratings to be different relative to the ratings of the mandatory agency H2: After accounting for sample selection bias, there is no difference between the mandatory and optional agencies' rating class. H2 is more relevant to our study, and an alternative to H2 is that there are differences in rating scales even after accounting for sample selection bias. They conclude that firms are more likely to obtain a third rating if they are large and experienced issuers in the capital markets. They find evidence that these optional agencies have laxer rating scales compared to two mandatory agencies. Their findings provide no evidence to suggest that an issuers' decision to obtain more than two ratings is influenced by

[74] Fitch Investor Services is the third highest credit rating agency in terms of rating coverage and began rating service in 1924.

[75] Moody's and S&P are the only two agencies that issue unsolicited credit ratings. These are called mandatory ratings by Cantor and Packer (1997).

these factors. This study provides a new method of estimating rating differences between the two big and two small rating agencies, but does not provide much analysis informing the differences between the two major agencies.

Pottier and Sommer (1999) study the credit ratings for insurers. Following the Cantor and Packer (1997) approach, they conduct a two-stage maximum likelihood estimation method. In the first stage they determine the decision to be rated, to control for selection bias, and in the second stage they estimate two separate models to observe rating differences between agencies and differences in rating determinants across agencies. They use a sample of insurer financial strength ratings and use three rating agencies A.M Best[76], Moody's and S&P's credit rating information. In the first stage probit regressions, they use a standard probit model to determine the decision to be rated by using the credit ratings from each agency as a dependent variable. They utilize explanatory variables such as statutory capital divided by total assets, net income divided by total assets, the percentage change in net premiums written between 1994 and 1995, the number of state licenses, the line-of-business, investments in speculative grade bonds divided by invested assets, common stock investments divided by invested assets, reinsurance divided by the sum of direct premiums written, whether the firm is publicly traded, and natural logarithm of total assets. In the second-stage, using the same set of variables, they estimate two separate models using the ordered probit estimation method. In one second stage model, they use credit ratings as dependent variables for three different rating agencies to observe differences in rating determinants. In another model they use ordered numbers to represent the rating differences among the three agencies. These three ordered differences demonstrate lower credit ratings, equal credit ratings and higher credit ratings by differences between A.M Best and S&P, A.M Best and Moody's and S&P and Moody's. In their rating determinants results they find only two variables, representing size and investment in junk bonds, are significant in the Moody's model, whereas a higher number of variables are significant using S&P and A.M Best ratings. This may suggest Moody's uses only a small number of factors available in public domain and relies more on private or qualitative information. In their other model, where they use rating differences as the dependent variable, they

[76] A.M. Best is a specialized rating agency focussing exclusively on insurer financial strength ratings.

find only two variables are significant in the model for A.M. Best compared to Moody's (size and line-of-business diversification). Also when comparing S&P against Moody's they discover six significant variables (common stock, Investments, size, capitalization, growth in premiums, profitability, and long-tail lines percentage). These results suggest rating agencies have different standards and that indeed they differ on the basis of the statistical significance attributed to the coefficients. The significant differences in the rating determinants suggest all three rating agencies use different proprietary models and allocate different weight to these factors resulting in split credit ratings. These results are only applicable to insurance business, as such the rating determinants differences are not applicable in corporate credit ratings.

Another hypothesis put forward to explain split ratings is proposed by Morgan (2002), who demonstrates that issuers with split credit ratings have more opaque assets. He argues that split ratings are more common in bond issues from financial institutions. Such asset opaqueness leads to greater analyst disagreement from the agencies. He concludes that split ratings tend to remain splits, as long as the assets for the firm remain opaque. Findings reveal that financial institutions having opaque assets will have a greater tendency to have split ratings. He investigates the pattern of disagreement between Moody's and S&P using their ratings on 7,862 new bonds issued publicly by U.S firms between January 1983 and July 1993. To test whether the disagreement is higher for banks, the study estimates both probit and ordered probit model regressions. Morgan (2002) finds that the agencies do indeed disagree more frequently and more widely over banks. Split rating between the two raters over banks is not symmetric, but lopsided, with Moody's lower on average.

Santos (2006) studies the impact of split credit ratings and state of the economy on bond yields. He first ascertains the determinants of split credit ratings between Moody's and S&P, and then he conducts analysis of these split credit ratings on bond yields. His sample includes 10,050 bonds issued during 1982 and 2002, and excludes financial firms. In the first section, he uses a dummy variable to identify split ratings at a notch level, and includes it as a dependent variable in a series of probit regressions. He uses the average rating of the two agencies as an independent variable to use as a proxy for creditworthiness. To find out if mid-quality issuers are more likely to obtain a rating split than issuers on either tail of the rating distribution he also considers a quadratic form of this proxy in his model specification. His study also includes a dummy to reflect the state of the economy, which indicates if the bond is issued during a recession[77]. He uses bond properties, for instance the maturity of the bond, the amount of an issue, whether the bond has a call option, a put option, or a sinking fund, whether it is a shelf bond, and finally whether it was privately placed, as control variables. In addition to bond specific features, he also includes issuer specific features such as its sector activity as defined by SIC[78] one-digit code, whether it is a public company, the number of times the company has issued bonds since 1970 and the length of time since the company's last bond issue. The results reveal a concave relationship between a split credit rating and bond creditworthiness when comparing the two linear and quadratic model specifications, the results reveal that the likelihood of a split credit rating is better explained by adding an additional quadratic form reflecting average rating. This shows that the likelihood of a split rating first increases and then decreases. In other words, an average bond rating in his sample is most likely to have a split. He also finds an insignificant coefficient on the recession dummy. In another model specification, when he uses an interaction term between a recession dummy and a proxy for creditworthiness, he finds the recession dummy to be significant. This shows that the mid-credit quality bonds are more likely to have a rating split than bonds on either tail of the distribution in terms of bond creditworthiness.

Livingston et al. (2007) further study the asset opaqueness issue on a sample of new bond issues between 1983 and 2000, a total of 1779 observations. They exclude financial firms, as Morgan (2002) relates financial firms' asset opaqueness to split credit ratings. They use accounting, opinion and market microstructure proxies to demonstrate asset opaqueness in firms, and employ a series of probit models to observe the impact of the selected variables on split credit ratings. In the first model they use selected proxies to show the impact of accounting and other variables on split credit ratings. In the second model they add the additional, ordinal S&P rating,

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[77] He uses period of recession on the basis of business cycle information available through The National Bureau of Economic Research (NBER).

[78] Standard Industrial Classification Codes attempt to classify industries according to similarities in products, services, and production and delivery systems. SIC Codes organize industries in an increasing level of detail ranging from general economic sectors (i.e. manufacturing, services) to specific industry segments (i.e. commercial sports, laundry businesses).

and in the final model instead of ordinal credit ratings they use cardinal rating dummies. The statistical significance of their asset opaqueness proxies shows that firms with more opaque assets have a higher probability of a split rating. Their second model suggests that there is no monotonic relation between credit risk and split ratings. However, the final model reveals that junk bonds are more likely to have split ratings than are investment grade bonds. In addition to split credit ratings, they also find that two thirds of the initially split-rated bonds remain split-rated four years after the initial issuance. Their results suggest that split rated bonds may be priced to offer additional risk premiums to compensate for the uncertainty regarding the issuing firm's fundamentals. Haggard et al. (2006) examine the opacity of a firm's information. The financial statements are prepared in accordance with accounting principles and regulations; there exists an issue regarding the quality of these statements. Haggard et al. (2006) reveals that lower quality financial reporting contributes to information uncertainty, which creates uncertainty in the risk assessment of rating agencies.

The literature on split credit ratings is somewhat inconclusive, and further research is required. A few areas that are not explored so far are the differences between splits on both a category level and notch level between two major agencies. Secondly, further research is required to include variables other than financials as determinants of splits. In the literature analyzing the determinants of credit ratings, many variables associated with governance issues are also associated with the credit ratings. These variables have not yet been utilized as potential determinants of splits between the two agencies. Evidence suggests (for instance, Morgan (2002)) that Moody's rates issuers lower on average, suggesting a more conservative approach from Moody's than S&P. However, in a few cases S&P is lower within a split. In this chapter, we study these differences in the context of the existing literature, by focusing on factors determining agencies to rate lower than other.

4.3 Data and Methodology

4.3.1 The Data and the Data Sources

Data is collected from a variety of sources for our data window from 1995 through 2009. The data set constitutes an unbalanced panel covering fifteen years. The selection of fifteen years of data span enables the study to cover a variety of stages in the business cycle. We not only witness recession period in the year 2001 and 2008-2009, but also witness high and steady economic growth in other years[79]. We select a portfolio of issuer firms from S&P 500[80], S&P 400[81] and S&P 600[82] index constituent firms. We limit our portfolio to these index constituent firms, because the variables we use in our models evidence some limitations in terms of data availability. The data for the G-Index is only available for the three above mentioned indices. We consider this sample to be a representative of the whole universe of corporate issuer firms, as the three indices involve large, medium and small size firms, accounting for around 85%[83] of the U.S. equity market share capital. Based on the availability of credit ratings and other data, our final sample produces an unbalanced panel over the fifteen years, consisting of 7234 firm-year observations. From these 7234 observations, we further filter our sample and exclude firms from the Financial and Utility sectors. Following Blume et al. (1998) and Ederington (1986) we exclude financial and utility industry firms, as they work under different regulations, and they are accessed using separate rating methodologies by the two agencies. After excluding financial and utility firms, our sample encompasses 5238 observations. We have 471 issuer firms in the year 2009 having credit ratings from both the agencies, and we track credit ratings history and other financials of these firms depending upon the data availability until 1995. This constitutes an unbalanced panel of 5238 firm-year observations. However, in the year 2009, our sample of 471 firms excluding financial and utility sectors, we have 276 (59%) issuers from S&P 500 index, 132 (28%) from S&P 400 index, and 63 (13%) from S&P 600 index.

[79] According to National Bureau of Economic Research (NBER), the 2001 recession lasted for eight month from March 2001 till November 2011, and 2007 lasted for eighteen months starting December 2007 till June 2009.

[80] The S&P 500 has been widely regarded as the best single gauge of the large cap U.S. equities market since the index was first published in 1957. The index has over US$ 4.83 trillion benchmarked, with index assets comprising approximately US$ 1.1 trillion of this total. The index includes 500 leading companies in leading industries of the U.S. economy, capturing 75% coverage of U.S. equities.

[81] The S&P MidCap 400 provides investors with a benchmark for mid-sized companies. The index covers over 7% of the U.S. equity market, and seeks to remain an accurate measure of mid-sized companies, reflecting the risk and return characteristics of the broader mid-cap universe on an on-going basis.

[82] The S&P SmallCap 600 covers approximately 3% of the domestic equities market. Measuring the small cap segment of the market that is typically renowned for poor trading liquidity and financial instability, the index is designed to be an efficient portfolio of companies that meet specific inclusion criteria to ensure that they are investable and financially viable.

[83] Source S&P website: http://www.standardandpoors.com/indices/main/en/eu

There are three stages in the data collection: the first involves obtaining data for the credit ratings from S&P and Moody's. We use Compustat (through WRDS) to extract data for S&P[84] long-term domestic issuer level firms. We use data from Bloomberg to collect long-term issuer level data for Moody's[85] credit ratings data. For both CRAs, we assign a rating to each specific firm as of December 31st of each sample year. As ratings may change during the year, we only consider credit ratings assigned as of end-December every year. Our portfolio has 1500 firms, but for the analysis, we only consider firms with ratings obtained from both the CRAs. Firms in our selected portfolio rated only by one rating agency S&P or Moody's, are not considered for inclusion in the analysis.

Financial Variables

The COMPUSTAT annual files are the source of data collection for computing financial ratios. We compute different accounting and financial ratios to indicate a firm's profitability, leverage, coverage and size. Previous studies[86] use different accounting ratios to show a firm's financial risk. Based on this prior literature, we select seven ratios to characterize a firm's leverage, coverage and profitability. The two leverage ratios in the study are (DLTT (total long-term debt) to total assets), and (DLTT+DLC (total long-term debt + debt in current liabilities) to Total Assets). Two coverage ratios are selected for each firm, (EBITDA (earnings before interest) to XINT (interest charge)) and (OIADP (operating income after depreciation) to XINT (interest charge)). Three profitability measures are computed: (OIBDP (operating income before depreciation) to Net Sales), (EBITDA (earnings before interest to sales) and (net income (loss) to total assets).

[84] The S&P's issuer credit rating is a current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations. This opinion focuses on the obligor's capacity and willingness to meet its long-term financial commitments (those with maturities of more than one year) as they come due.

[85] Moody's credit ratings are opinions of the credit quality of individual obligations or of an issuer's general creditworthiness (without respect to individual debt obligations or other specific securities).They address the possibility that a financial obligation will not be honoured as promised. Such ratings use Moody's Global Scale and reflect both the likelihood of default and any financial loss suffered in the event of default.

[86] See for instance, Horrigan (1966), West (1970), Pogue and Soldofsky (1969), Pinches and Mingo (1973 and 1975), Altman and Katz (1976), and Kaplan and Urwitz (1979), and Blume et al. (1998)

As mentioned above, a number of other studies document a positive relationship between firm size and credit ratings (See for instance, Kaplan and Urwitz (1978) and Blume et al. (1998)). We measure firm size by using the natural logarithm of total assets, using COMPUSTAT annual files to collect the values for total assets. Total assets are also used in the computation of certain profitability measures. We follow past research by including the equity beta as a measure of systematic risk. Blume et al. (1998), for example, say that a firm will be less able to service its debt for given values of its accounting ratios as its equity risk increases. Firm level betas are obtained from CRSP indices/deciles: portfolio assignments. We use the year-end-beta daily file to collect firm level beta values for each year. Company based beta's are available for NASDAQ and NYSE/AMEX.

Governance Variables

In our study, we also use three governance related variables. These three governance related variables are: the G-Score developed in Gompers et al. (2003), the percentage of the company's stock held by institutions, and finally the percentage of the board of directors who are not also officers of the firm. We collect data for the G-Score from the RiskMetrics-Governance legacy database. This is updated every three years. We use the RiskMetrics-Directors Legacy to collect for the percentage of the board of directors who are not also officers of the firm. The database starts from 1996 onwards; we note that we have repeated the percentages reported for 1996 in 1995. Since, changes in the composition of the board are not very frequent, we do not expect any significant changes in one year. We use Thomson Reuters-Institutional (13F) holdings-s34 to collect data for stock held by Institutions. The December database for each of the years 1995-2009 is used for our analysis.

Other Variables

On the basis of their failure to predict major corporate failures such as Enron and WorldCom credit agencies are criticized for having a potential conflict of interest. The current market structure of the "issuer pay model" further reinforces this criticism, as agencies are also criticized for acting in favour of their clients. In our study, we also include different proxies to attempt to account for this general criticism and potential conflict of interest within the rating agencies business. These proxies may help us to further explain rating splits across the two agencies, as if they can capture any subjective elements which lie behind split ratings.

The first variable we observe relates to potential rating shopping behaviour within issuer firms. We use a dummy variable equal to one for a firm having three or more ratings and zero otherwise. The two rating agencies we use follow an "issuer pay model", so it is possible that issuers with three or more ratings seek additional ratings in order to enhance the credit rating. A firm's credit rating history is obtained from Bloomberg. Any impact of rating shopping dummy on rating splits may demonstrate subjectivity within rating system. Becker and Milbourn (2011) find evidence of rating inflation by Moody's and S&P in response to increased competition following entrance of the third largest rating agency, Fitch. The inclusion of rating shopping dummy would demonstrate the impact of rating shopping on the likelihood of having a split rating.

We use a dummy for the Regulation FD legislation, implemented on October 23, 2000, which prohibits U.S. public companies from making selective, non-public disclosures to favoured investment professionals. This regulation has an exclusion enabling rating agencies to preserve their access to non-public information. Jorion et al. (2005) show that after the introduction of regulation FD, the information effect of credit ratings on stock prices, as measured by the impact of a credit downgrade and or upgrade appears to be much greater. In order to take account of this possible effect, we incorporate a dummy for the post- and pre-regulation FD period. A zero dummy variable is used for the pre-regulation FD, and the dummy is set equal to one for the post-FD period. The sign on this dummy variable indicates if regulation FD initiated any change in the rating agencies approach towards assigning firm ratings. The sign and significance of this dummy variable informs us as to whether the introduction of this favoured regulation increases or decreases the occurrence of rating splits,

We also use a proxy to capture stages in the business cycle. We use the annual percentage growth of GDP as a proxy for the business cycle. Data is collected for GDP growth percentages from the World Bank website, where historical data is available for member countries. A priori, we do not necessarily expect a rating agency to follow different rating standards, but a negative (positive) sign would suggest some validity to the criticism they become stricter(lenient) during recession periods.

4.3.2 Methodology

We initiate our empirical analysis by presenting a summary data description for our unbalanced panel of 5238 firm-year observations from 1995 through 2009. We also track the persistence of our split-rated issuers and non-split rated issuers within our sample, using the Livingstone et al. (2007) method to track split rating transitions during our data window. To track the rating transitions, we further divide our sample into four sub-samples. This is undertaken as our sample is an unbalanced panel of firm-year observations. We track the rating history of only those issuer firms that are index constituent of S&P500, S&P 400 and S&P 600 indices at the time of our data collection in December 2010. Since, we do not have fifteen years of data for each issuer firm; we have a different period of rating history for each firm during the fifteen years of our data window. Our four samples are: 1 firms with all the fifteen years of data 1995 through 2009, 2 firms with twelve years of data 1998 though 2009, 3 firms with nine years, 2001 through 2009, and 4 firms with six years from 2004 through 2009. Each of these four sub-sample is then further divided into three groups. First, for each sample we analyse issuers that have congruent ratings at the beginning of each sample period. A second group comprises issuers having splits at notch level at the beginning of each sample period. Finally, we have a group of issuers that have splits at the category level at the beginning of the sample. We present all these rating transitions during the four sub-samples graphically. To have sufficient observations in each sub-sample, we only consider these four sub-samples. For instance, an issuer having fourteen years of rating history is considered in the year 1998-2009 sample and is grouped in a way that we only start its rating history from the year 1998-2009. This way we are able to obtain enough observation in each sub-sample to help us further substantiate our findings.

We then present the estimates from the bivariate model explained below. We are the first to use bivariate probit estimation methods in credit ratings settings; however, previous literature` documents its use in different academic areas. For instance, Cotei and Farhat (2011) use bivariate probit model to study firms' debt-equity choice.

They utilise first stage regressions to have firms' decision to have an external or internal funding. In the second stage, within external funding, they study choice between firms' decision to issue debt or equity. Similarly, Rayton (2006) uses bivariate model to observe link between employees' commitment to their organizations in the first stage, and job satisfaction in the second stage.

In our study, the bivariate approach allows us for the possibility that a CRA's decision towards a split rating and whether to place lower (or above) within a split are jointly determined, rather than the result of independent processes. We use two separate dependent variables to estimate two bivariate models. In the first model, we take differences at both notch level and category level as our dependent model. In the second model, we only consider category level differences to be a split, and use split dummies as our dependent variable in the first stage of our model. In both models, when conducting the second stage probit regressions we use S&P lower within a defined split as a dependent variable. The model is explained further below. Next section describes our bivariate probit model in some detail, but focuses on the practical implications of the approach. Interested readers may consult Greene (2003) for full technical details of the bivariate probit approach.

The Model

Let $Split_{S\&P\ lower}$ be a vector of observations of the i_{th} firm within our j_{th} sample of firms having S&P ratings lower than Moody's in a split. Let W be a vector of independent variables that influence S&P lower ratings within our j_{th} firms.

We can specify this equation by:

$$Split_{S\ \&P\ lower}=\delta_j\, W+\varepsilon_j \qquad (4.1)$$

where δ_j is a vector of coefficients and ε_j is a disturbance term in the sample of firms which both have a split rating and also have S&P being lower in the split.

There is a sample selection issue evident in the equation (4.1). The whole sample contains firms that have congruent ratings as well as split credit ratings from the two agencies. Split rated firms are further sub divided into two groups, where S&P rating is lower, and where Moody's ratings is lower respectively.

The equation with Split $_{\text{S\&P Lower}}$ (Split $_{\text{Moody's Lower}}$) within a sample of issuers is only observed when there is a split credit rating, and within that split we have S&P (Moody's) rating lower than Moody's (S&P). These observations are all part of a non-random process, and our specification selection should be able to address this issue. To resolve this issue, we specify a bivariate probit model, which is discussed in the following paragraph.

Let y_1^* represent the propensity of firm 1 to have a split rather than congruent credit ratings from Moody's and S&P. This propensity to have split credit ratings is given in equation (4.2):

$$y_1 = \begin{cases} 0 \text{ if } y_1^* \leq 0 \\ 1 \text{ if } y_1^* > 0 \end{cases} \tag{4.2}$$

where $y_1^* > 0$ shows that firms with a higher propensity to have a split credit ratings from both the agencies.

Firms having higher propensity to have a split credit ratings are subsequently further divided into two categories. Let y_2 represent the corresponding propensity to have S&P a lower credit rating within split rated firms. This shows that y_2 is only observed when we have a split credit ratings within our sample i.e. y_1=1. The term y_2 shows whether S&P is rated lower within split ratings; value y_2=1 is assigned to a firm with S&P lower ratings and y_2=0 to a split rated firm rated lower by Moody's. This is shown in equation (4.3).

$$y_2 = \begin{cases} 0 \text{ if } y_2^* \leq 0 \\ 1 \text{ if } y_2^* > 0 \end{cases} \tag{4.3}$$

The two equations (4.2) and (4.3) represent two interrelated decisions by the rating agencies. We are interested in modelling a rating agencies decision (i) to have a split rating and (ii) to place higher or lower compared to the other major agency. We consider the following specification of the Bivariate Probit Model to allow us model these two interrelated binary decisions.

Suppose Split$_{\text{S\&P lower}}$ is only observed when y_1=1 and y_2=1, while Split$_{\text{Moody's lower}}$ is only observed when y_1=1 and y_2=0. The specification model for a firm i is shown in equation (4.4).

$$y_1 = \alpha X_1 + u_1, y_1 = \begin{pmatrix} 1 & \text{if } y_1^* > 0 \\ 0 & \text{Otherwise} \end{pmatrix}$$
$$y_2 = \beta X_2 + u_2, y_2 = \begin{pmatrix} 1 & \text{if } y_2^* > 0 \\ 0 & \text{Otherwise} \end{pmatrix} \tag{4.4}$$
$$S_i = \delta_i W + \varepsilon_j \begin{cases} E(\text{Split}_{\text{S\&P lower}} | W, y_2 = 1, y_1 = 1) \\ E\left(\text{Split}_{\text{Moody's Lower}} | W, y_2 = 0, y_1 = 1\right) \end{cases}$$

where α, β, δ vectors of coefficients, X_1, X_2 and W are are vectors of independent variables and μ_1, μ_2, ε_j are disturbance terms.

Equation (4.4) summarizes our bivariate probit model. First, we have a preference over ratings with splits and no splits, and then we have a preference of one agency rating lower in a split. If the error terms in two equations concerning the decision to have a split, and whether to have lower or higher in a split are independent, i.e. Cov $[u_1,u_2]=0$, we can just estimate two separate probit models. Since, the two decisions are interrelated the error can be written as:

$$\begin{aligned} u_1 &= \eta_s + \varepsilon_1 \\ u_2 &= \eta_s + \varepsilon_2 \end{aligned} \tag{4.5}$$

In other words the errors in each model consist of one part $\varepsilon_1, \varepsilon_2$ that is unique to that model, and another part η_s that is common to both. In this particular case, the normal probabilities are non-independent probabilities, as they depend upon the common value of η_s. As such, we are required to calculate the joint probabilities for non-independent events, which is given by:

$$P_r(y_1 = 1, y_2 = 1) \begin{aligned} &= P_r(y_1 = 1 | y_2 = 1) \times P_r(y_2 = 1) \\ &= P_r(y_1 = 1) \times P_r(y_2 = 1 | y_1 = 1) \end{aligned} \tag{4.6}$$

There is no convenient formulation of the bivariate choice model based on the logistic distribution (Greene and Hensher (2009)). Typically a bivariate normal distribution is used, and we follow the same procedure by assuming a bivariate normal distribution for the two standard-normally distributed u_s. Their joint density is:

$$\Phi(u1, u2) = \frac{1}{2\pi\sigma_{u1}\sigma_{u2}\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2}\left(\frac{u_1^2 + u_2^2 - 2\rho u_1 u_2}{1-\rho^2}\right)\right] \tag{4.7}$$

where ρ is a correlation parameter denoting the extent to which the two u_1, u_2 covary. Their joint cdf is:

$$\int u_1 \int u_2\, \Phi_2(u_1, u_2, \rho) du_1 du_2 \qquad (4.8)$$

We use the Φ_2 distribution to estimate our bivariate probit models. In other words, typically we assume that the error terms are independent and identically distributed as standard bivariate normal with correlation coefficient ρ.

$$\begin{gathered} E\{u_1|x_1, x_2\} = E\{u_2|x_1, x_2\} = 0 \\ Var\{u_1|x_1, x_2\} = Var\{u_2|x_1, x_2\} = 0 \\ Cov\{u_1, u_2|x_1, x_2\} = \rho \end{gathered} \qquad (4.9)$$

The bivariate probit model utilizes maximum likelihood estimation (MLE), the parameter ρ_{12} estimates the correlation between the error terms of the two equations explained in equation (4.4). If the MLE estimate of the correlation coefficient ρ_{12} is significant, then we prefer the Bivariate probit model over independent probit estimations. This is generally referred to as $u_1, u_2 \sim \phi_2(0,0,1,1,\rho)$. Given this, we are now able to make probability statements about y_i

$$P_r(y_{1i} = 1, y_{2i} = 1) \begin{array}{l} = \int_{-\infty}^{u_{1i}} \int_{-\infty}^{u_{2i}} \phi_2(x_1\beta_1, x_2\beta_2; \rho) du_1 du_2 \\ = \Phi_2(x_1\beta_1, x_2\beta_2, \rho) \end{array} \qquad (4.10)$$

The log-likelihood is just the sum over the four possible transition probabilities, multiplied by their associated probabilities. The log likelihood for the bivariate probit model is:

$$\begin{gathered} \ln L = \sum_{i=1}^{n} \ln\Phi_2\left(x_1\beta_1 . x_2\beta_2, \rho\right) \\ +y_{i1}(1 - y_{i2})\ln\left[\phi(x_1\beta_{1)} {}_{-} \Phi_2(x_1\beta_1, x_2\beta_2, \rho)\right] \\ +(1 - y_{i1})y_{i2}\ln[\phi(x_2\beta_2) - \Phi_2(x_1\beta_1, x_2\beta_2, \rho)] \\ +(1 - y_{i1})(1 - y_{i2})\ln[1 - \phi(x_1\beta_1) - \phi(x_2\beta_2) - \Phi_2(x_1\beta_1, x_2\beta_2, \rho)] \end{gathered} \qquad (4.11)$$

where Φ_2 denotes the bivariate standard normal cdf with correlation coefficient ρ and ϕ is the univariate standard normal cdf.

In equation (4.11) $\phi(x_1\beta_{1)}{}_{-}\Phi_2(x_1\beta_1, x_2\beta_2, \rho)$ is just the probability that y_1 =1 minus the probability that y_1=y_2=1, in other words in captures $\Pr(y_1 = 1, y_2 = 0)$.

We also estimate the marginal effects by computing the derivatives of joint probability of having a split and having S&P lower within a split by following equation:

$$\mathrm{Prob}\{y_1 = 1 y_2 = 1 | x_1 x_2\} = \Phi_2(x_1\beta_1, x_2\beta_2, \rho) \qquad (4.12)$$

4.4 Empirical Results

This section presents and discusses the empirical results of our study. We begin the empirical section by presenting descriptive statistics of our sample of 5238 firm-year observations through our data window, 1995-2009. We then explain the characteristic persistence of split credit ratings through graphical presentation of rating transitions within our four sub-samples. Finally, we present our two-stage bivariate probit regression models, first by using splits at the notch level as the dependent variable, and then using splits at the category level as the dependent variable. We also compare the two bivariate probit models and draw conclusions relating to our findings.

4.4.1 Descriptive Statistics

Our sample has a total of 5238 firm-year observations. Of these split ratings comprise 2644 observations at the notch level and 1201 observations at category level. Table 4.1 provides the frequency of split credit ratings within our whole sample over our data window, 1995-2009. The frequency of splits is further explained by allocating our sample into two types of splits. Columns 2-4 present the frequency and percentage of splits at a category level, whereas, columns 5-7 explain frequency of splits at a notch level. We find that at a category level the total number of splits is 22.93%, increasing to 50.48% at the notch level. If we compare the percentage of splits throughout our data window, other than in 1995, we do not see any significant differences each year. Similarly, in case of splits at the notch level, the highest percentage of splits is observed in the year 1995. Figure 4.1 also presents the results of percentage differences within splits at category and notch level. We can see in the figure that notch level differences remain close to 50%, while category level splits are close to 20% over-time. Only throughout 2000-2001 do we find that the percentage in terms of category level splits is below 20%. At notch level, this percentage varies around the 50% level.

In figure 4.1, we show the graphical presentation of percentage of splits ratings through fifteen years of our data. If we compare the movement of splits at the category and notch level, we find that the overall trends differ from year 2000 onwards; category splits go down, whereas, notch level splits go up.

In the case of category level splits, we find that the percentage of splits goes lower than 20% on only one occasion. In case of notch level splits, we find these within our data window generally fluctuates around the 50% mark throughout. The variation is more pronounced with notch level splits.

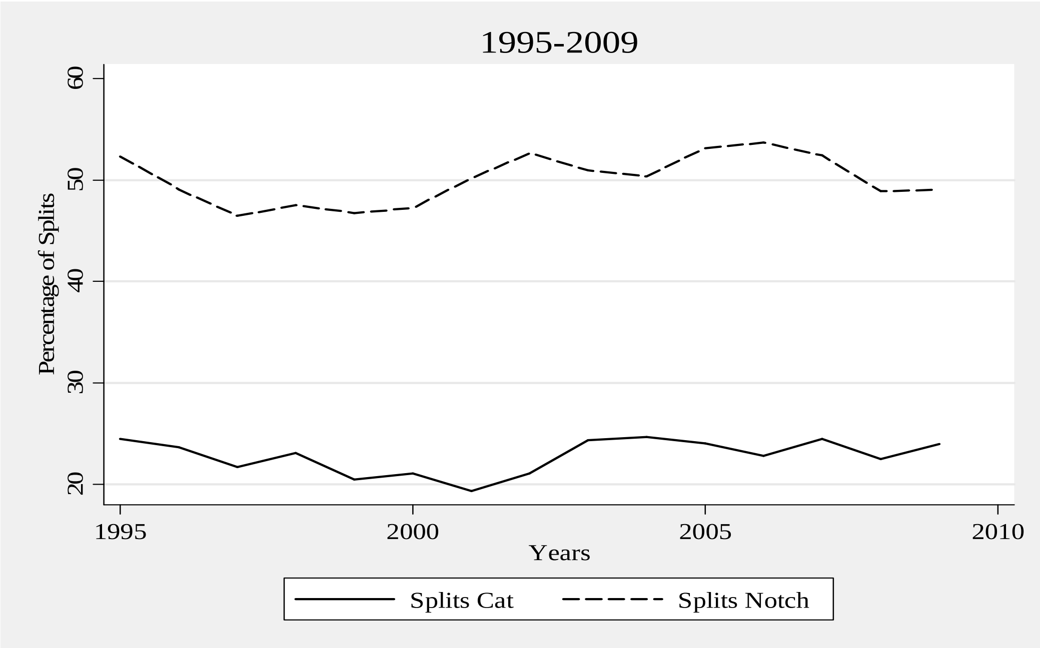
Table 4.1 Frequency/Percentage Distribution of Splits Over Time

The table reports the frequency of split credit ratings comparing S&P and Moody's credit rating agencies. The sample consists of 5238 observations over fifteen years 1995 through 2009. Split credit ratings are distributed based on the splits at the category level and splits at the notch level. Category difference occurs when an AA credit rating is different from A, and the notch level splits are when AA is different from AA+, and similarly through all rating grades.

Years	Category Level Splits			Notch Level Splits		
	No Splits	Splits	Percentage of Splits	No Splits	Splits	Percentage of Splits
1995	158	54	24.47%	101	111	52.35%
1996	168	52	23.64%	112	108	49.09%
1997	177	49	21.68%	121	105	46.46%
1998	217	65	23.05%	148	134	47.52%
1999	233	60	20.48%	156	137	46.76%
2000	244	65	21.04%	163	146	47.25%
2001	254	61	19.37%	157	158	50.16%
2002	285	76	21.05%	171	190	52.63%
2003	276	89	24.38%	179	186	50.96%
2004	308	101	24.69%	203	206	50.37%
2005	316	100	24.04%	195	221	53.13%
2006	345	102	22.82%	207	240	53.69%
2007	343	111	24.45%	216	238	52.42%
2008	355	103	22.49%	234	224	48.91%
2009	358	113	23.99%	240	231	49.04%
Total	4037	1201	22.93%	2594	2644	50.48%

Figure 4.1 Percentage of Splits Over Time (1995-2009)

Figure shows the percentage of split credit ratings comparing S&P and Moody's credit rating agencies. The sample consists of 5238 observations over fifteen years 1995, through 2009. Split credit ratings are distributed based on the splits at the category level and splits at the notch level. Category difference is when for example AA credit rating is compared to an A or AAA, and the notch level splits are when AA is compared to AA+ and AA-, and similarly through all ratings grades.



In table 4.2, we present the percentage of splits categorized on the basis of The GICS[87]. We find the highest percentage of splits at category level in the consumer discretionary and health sectors and the lowest level in the consumer staples and telecommunication sectors. At the notch level splits, we find that the highest percentage of splits is observed in the health sector and the lowest in the Industrial sector. Other than the health sector at notch level splits, we do not find significant differences between the sectors and the numbers remain generally close to the overall percentage of 50.00%. Recall that we do not include financial and utility sector firms in our sample, for the reason that prior studies have associated splits with asset opacity. For instance, Morgan (2002) reports that financial firms are more

[87] The Global Industry Classification Standard (GICS) was developed by MSCI, a premier independent provider of global indices and benchmark-related products and services, and S&P, an independent international financial data and investment Services Company and a leading provider of global equity indices. The GICS structure consists of 10 sectors, 24 industry groups, 68 industries and 154 sub-industries.

likely to have split credit ratings. Similarly Livingstone et al. (2007) suggest that there is a causal link between asset opaqueness and split ratings. In our sample, we find that splits are extensively reported in all eight remaining sectors as well.

Table 4.2 Frequency/Percentage Distribution of Splits Over GICS Industry Classification

The table reports the frequency distribution of split credit ratings between S&P and Moody's credit rating agencies over GICS industry classification. The sample consists of 5238 observations from S&P 500, S&P 400 and S&P 600 indices. The sample excludes the financial and utility sectors firms. Split credit ratings are distributed based on the splits at the category level and splits at the notch level. Category difference is when AA credit rating is different from A, but not from AA+. The notch level splits are when AA is different from AA+, and similarly for ratings grades.

GICS Industry Classification	Category Level Splits			Notch Level Splits		
	Frequency of Non-Splits	Frequency of Splits	Percentage of Splits	Frequency of Non-Splits	Frequency of Splits	Percentage of Splits
Energy	420	101	19.39%	271	250	47.98%
Materials	526	146	21.73%	347	325	48.36%
Industrial	912	258	22.05%	641	529	45.21%
Consumer Discretionary	824	306	27.08%	527	603	53.36%
Consumer Staples	446	84	15.85%	277	253	47.74%
Health	471	168	26.29%	229	410	64.16%
Information Technology	361	125	25.72%	256	230	47.33%
Telecommunications	77	13	14.44%	46	44	48.89%
Total	4037	1201	22.93%	2594	2644	50.48%

Table 4.3 reports the mean statistics for our financial and governance related variables distributed in terms of splits defined at the category level. Panel A reports the mean statistics for variables used in the study for the firms where the two agencies have congruent ratings. Panel B and C report the mean statistics of split credit ratings at a category level, and explains the mean statistics based on S&P and Moody's credit ratings. The statistical significance shown with the means is the differences between the split rated sample and non-split rated sample, for instance statistical significance shown in panel B is the difference between the means of non-split rated sample (Panel A) and split rated sample explained by S&P ratings (Panel C). Similarly, Panel D reports the differences in means and t-Test results within split rated sample explained by S&P and Moody's results (differences in panel B and C). The results in table 4.3 suggest that in the highest AAA rating category, issuer firms with non-split ratings are larger in size, have higher coverage ratios, a lower leverage

measure and higher profitability compared to the same group of issuers with split ratings. In terms of governance related variables, if we only consider AAA rated firms, we find that firms with split ratings have a lower G-Score, percentage of institutional investment and percentage of outside directors on board as compared to split-rated issuers. However, when looking at the lowest credit rating category B or less, we do not observe any consistent trends between non-split and split rated firms. Issuers with non-split credit ratings have a tendency toward lower asset size, coverage ratio, and leverage ratios as compared to split rated firms. They also have a higher market beta. In the case of profitability and the governance variables, we also find variable trends. Non-split rated firms have a higher mean profitability measure, and G-score compared to split rated firms with S&P ratings, but lower if compared to Moody's ratings.

If we look at the t-Test results, we mostly find the differences between non-split and split rated sample are statically significant. In panel B, except AAA rating category, the size measure is statistically different from the non-split sample in panel A. Whereas in Moody's case the size measure is not statically different from panel A. This shows that the S&P has different standards for the size measure, resulting in splits. Similarly, other significant factors in differences in means between non-split sample and split sample are more visible in governance related variables. This shows that governance related differences in two agencies are a major factor in having split ratings. In panel D, we show the actual differences in two agencies split rated sample means and their statistical significance. We only present results for five categories, as no firm rated Aaa by Moody's is rated lower by S&P. We observe that the size measure is statistically significant at 1% level in all the five categories, similarly in leverage measure we find more differences in mid-level rating categories (BBB (Baa) and BB (Ba)). As per t-Test results shown in panel B and C, we find governance related variable differences are statistically significant between the two agencies. We discuss the significance of these measures in split ratings in our next section, where we discuss our results from bivariate probit model.

Table 4.3 Mean Statistics for Selected Variables, Splits at Rating Category Level

The table presents mean statistics for our eight selected variables distributed on the basis of splits and non-splits between the two credit rating agencies. The splits here are defined when the rating category is different, so for instance AA is different from A, but not from AA+. These variables are based on financial information of the company and also include three governance related variables. The sample consists of 5238 observations spanning fifteen years of data 1995 through 2009. Panel A reports mean statistic for 4037 observations, where the credit ratings are congruent. Panel B reports the mean statistics distributed on S&P credit ratings and Panel C reports mean statistics distributed on Moody's credit ratings. There are 1201 observations of splits at category level, where Moody's credit rating is lower for 941 observations and S&P's for 260 observations. t-Tests are performed to test the differences in the variable means between the split rated and non-split rated samples, and within splits differences in S&P and Moody's ratings. In panel B and C, the statistical significance shown with the symbol * depicts the differences in means between split and non split sample, while panel D reports the actual differences in means and statistical significance between split rated sample sorted by ordered S&P ratings and by ordered Moody's ratings.

Credit Rating Category	Size Measure (Log Assets)	Market Beta	Coverage Measure	Leverage Measure	Profitability Measure	G-SCORE	Percentage of Institutional Investment	Percentage of Outside Directors
Panel A: Mean Statistics for Non-Splits observations on selected variables								
AAA	10.90	0.86	31.17	0.10	0.12	9.70	0.67	0.84
AA	9.63	0.87	23.97	0.15	0.11	10.22	0.76	0.82
A	9.11	0.95	18.09	0.18	0.08	10.20	0.70	0.79
BBB	8.55	1.04	10.97	0.22	0.05	10.21	0.68	0.69
BB	7.95	1.27	6.92	0.32	0.03	9.05	0.64	0.60
B or Less	7.47	1.45	3.77	0.39	-0.03	9.18	0.59	0.59
Total	8.64	1.07	12.96	0.23	0.06	9.92	0.68	0.71
Panel B: Mean Statistics for Split credit ratings based on S&P Credit ratings								
AAA	10.47	0.81	33.76	0.10	0.11	9.16	0.70	0.86
AA	9.21***	0.77**	19.21**	0.16	0.08***	11.49***	0.69***	0.72***
A	8.71***	0.93	15.88**	0.19	0.08	9.90	0.64***	0.67***
BBB	8.22***	1.03	9.49***	0.24*	0.04**	9.58***	0.69	0.64***
BB	7.76***	1.35**	6.98	0.29***	0.03	9.28	0.64	0.58***
B or Less	8.05***	1.44	5.57**	0.33*	-0.05	7.69***	0.65***	0.68***
Total	8.25	1.13	10.71	0.24	0.04	9.55	0.66	0.64
Panel C: Mean Statistics for Split credit ratings based on Moody's Credit ratings								
Aa	9.72	0.82	24.02	0.16	0.10	8.61	0.78	0.87
A	9.07	0.86	17.97	0.19	0.08	10.80***	0.72	0.74**
Baa	8.44	1.06***	14.00	0.19	0.06	9.63***	0.62	0.64***
Ba	8.00	1.06***	7.82*	0.24***	0.03	9.13***	0.65***	0.60***
B or Less	7.75	1.38***	5.44**	0.32***	0.02***	9.36	0.65***	0.58***
Total	8.25	1.13	10.71	0.24	0.04	9.55	0.66	0.64
Panel D: t-test for difference in Mean Statistics between Split Rated Sample. (Moody's-S&P)								
AA	0.50***	0.05	4.81**	0.01	0.02**	2.88***	0.09***	0.15***
A	0.37***	0.07	2.08	0.01	0.001	0.90***	0.07***	0.07***
BBB	0.21***	-0.03	4.50***	0.05***	-0.01**	-0.04	0.07***	-0.03
BB	0.23***	0.28***	-0.83	0.05***	-0.01	0.15	-0.01	-0.02*
B or Less	0.303**	0.06	0.13	0.01	-0.07***	-1.68***	0.01	0.11***

***,**,* indicate significance level at 1%, 5%, and 10% respectively

Table 4.4 presents the mean statistics for our selected variables, including financial and governance variables, and further divides the samples based on notch level splits. While table 3 explains mean statistics based on category level differences, in table 4 we only consider notch level splits. In this sample, we have almost equal number of observations in both the split and non-split samples. Note there are no observations within panel C in the Aaa rating category, as any issuer rated Aaa by Moody's is not rated below AAA by S&P. In terms of the size measure, we find that non-split ratings sample in case of BBB ratings is exactly equal to panel C ratings based on Moody's distribution. In other categories we find that Moody's has more stringent standards in placing firms in different categories. In the case of the coverage ratio, we observe that for AAA and BBB ratings, the mean coverage ratio of non-split issuers is close to that in panel B based on S&P ratings. However, we find that in other categories, Aa, A, BB and B or less, the mean values of non-split rated issuers are close to the mean values of splits based on Moody's ratings. In case of the G-Score measure, we find that our mean values in panel A are close to the mean values in the panel C in the first three categories. However, we do not find any consistency in terms of similar trends in the split and non-split sample. Similarly, in the final column of table 4, we find that the mean of the percentage of outside directors' variable in each rating category is close to that from the Moody's sample of split rated firms.

The statistical significance shown with the means is the differences between the split rated sample and non-split rated sample, for instance statistical significance shown in panel B is the difference between the means of non-split rated sample (Panel A) and split rated sample explained by S&P ratings (Panel C). Similarly, Panel D reports the actual differences in means and t-Test results within split rated sample explained by S&P and Moody's results (differences in panel B and C). If we look at the statistical significance of differences in means between non split rated sample (Panel A) and (Panel B and C), we find statistical significant means in both the financial and governance variables. In terms of profitability measure, we find the differences in means in both panel B and C is not statistically different. However, in all other four financial variables, we find the differences in means of non-split and split ratings are statistically significant in most of the observations. The differences in means of three governance related variables are also statistically significant.

In panel D, we report the actual differences in means of split-rated sample explained by S&P ratings in panel B and explained by Moody's ratings in panel C. We do not find any consistent trend, as size measure is significant in three categories and as insignificant in two other. However, in terms of governance related variables, we find more evidence of statistical differences in means. We discuss the statistical significance of all these measures on the likelihood of splits in our next section, where we discuss our results of bivariate probit model.

Table 4.4 Mean Statistics for Selected Explanatory Variables, Splits at Notch Level

The table presents mean statistics for our eight selected variables distributed on the basis of splits and non-splits between the two credit rating agencies. The splits here are defined when credit ratings are different at notch level, for instance AA+ is different from AA-.These variables are based on financial information of the company and also include three governance related variables. The sample consists of 5238 observations spanning fifteen years of data 1995 through 2009. Panel "A" reports mean statistic for 2,594 observations, where the credit ratings are congruent at notch level. Panel "B" reports the mean statistics distributed on S&P credit ratings and Panel "C" reports mean statistics distributed on Moody's credit ratings. There are 2644 observations of splits at notch level, where Moody's credit ratings is lower on 1929 observations compared to S&P's for 715 observations. t-Tests are performed to test the differences in the variable means between the split rated and non-split rated samples, and within splits differences in S&P and Moody's ratings. In panel B and C, the statistical significance shown with the symbol * depicts the differences in means between split and non split sample, while panel D reports the actual differences in means and statistical significance between split rated sample sorted by ordered S&P ratings and by ordered Moody's ratings.

	Size Measure (Log Assets)	Market Beta	Coverage Measure	Leverage Measure	Profitability Measure	G-SCORE	Percentage of Institutional Investment	Percentage of Outside Directors
Panel A: Mean Statistics for Non-Splits observations on selected variables								
AAA	10.90	0.86	31.17	0.10	0.12	9.70	0.67	0.84
AA	9.19	0.91	24.38	0.14	0.10	9.89	0.78	0.83
A	9.07	0.95	18.31	0.18	0.08	10.25	0.71	0.78
BBB	8.53	1.08	10.73	0.22	0.05	10.31	0.68	0.70
BB	7.84	1.29	7.05	0.33	0.03	8.81	0.64	0.59
B or Less	7.30	1.33	4.66	0.39	0.00	9.38	0.59	0.58
Total	8.63	1.08	13.35	0.23	0.06	9.96	0.68	0.71
Panel B: Mean Statistics for Split credit ratings based on S&P Credit ratings								
AAA	10.47	0.81	33.76	0.10	0.11	9.16	0.70	0.86
AA	9.61***	0.81**	21.67	0.16	0.09	10.92***	0.72**	0.77***
A	9.00	0.93	16.91**	0.20***	0.08	10.01*	0.67***	0.75***
BBB	8.44*	0.99***	10.69	0.23*	0.05	9.86***	0.67	0.66***
BB	7.90	1.30	6.88	0.29***	0.03	9.32***	0.64	0.60
B or Less	7.82***	1.51**	4.07	0.37	-0.05***	8.41***	0.61	0.64***
Total	8.47	1.09	11.56	0.24	0.05	9.72	0.66	0.67
Panel C: Mean Statistics for Split credit ratings based on Moody's Credit ratings								
Aa	9.87***	0.84	23.79	0.15	0.11	9.86	0.76	0.83
A	9.15	0.91*	17.70	0.20***	0.08	10.32	0.70	0.78
Baa	8.53	1.00***	12.32***	0.21	0.05	9.89***	0.65***	0.67***
Baa	8.05***	1.16***	7.25	0.27***	0.03	9.26***	0.65	0.62***
B or Less	7.73***	1.42	4.91	0.34***	0.00	9.29	0.64***	0.58
Total	8.47	1.09	11.56	0.24	0.05	9.72	0.66	0.67
Panel D: t-test for difference in Mean Statistics between Split Rated Sample. (Moody's-S&P)								
AA	0.258**	-0.025	-2.12	0.01	0.01**	1.05***	-0.03**	-0.06***
A	0.15**	0.02	0.79	-0.01	0.01	0.31*	0.03***	0.03***
BBB	0.09	0.01	1.63***	0.02***	0.01	0.03	0.02***	0.01
BB	0.15***	0.14***	0.37	0.02***	0.01	0.06	0.01	0.07*
B or Less	0.09	0.09	0.84*	0.03*	0.05***	0.87***	0.03**	0.05***

***,**,* indicate significance level at 1%, 5%, and 10% respectively

Table 4.5 explains our data on the basis of the frequency and the percentage of splits in terms of rating categories. The notch level differences are also explained through category level division. The first two columns pertain to the category level splits, and the last two columns explain the frequency of splits at the notch level. If we look at first two columns, we find that in panel A, for S&P, the highest frequency of splits at the category level is observed in the BB rating category. In the case of Moody's rating distribution, we find that the highest percentage and frequency of splits is observed in the lowest rating category, B or below. In both panel A and B, we find that second level highest percentage in terms of category level splits is observed in the mid rating category BBB (Baa). In case of notch level splits, the mid-level category BBB (Baa) contains the highest level of splits. The lowest split levels are observed in the upper most and lowest category. If we compare the two columns of category level to the two columns of notch level splits, we find that the frequency and percentage of splits at the notch level and at the category level are different. In panel A we find that the highest percentage of splits is observed within BB at category level, and at BBB for notch level. In panel B we have the highest percentage of splits at category B or below, and at notch level we have the highest percentage in the Baa category.

Table 4.5 Frequency of Split Credit Ratings at Notch Level and Category Level Credit Ratings

The table presents the frequency of split credit ratings distributed in terms of rating category. The splits are defined at notch level splits when AA+ is different from AA- and at rating category level when AA is different from A, but not from AA- or AA, and similarly through all ratings grades.

Ratings	Category Level Splits		Notch Level Splits*	
	Frequency	% Splits	Frequency	% Splits
Panel A: Frequency of Splits with S&P Ratings				
AAA	19	1.58%	19	0.72%
AA	95	7.91%	211	7.98%
A	232	19.32%	589	22.28%
BBB	340	28.31%	884	33.43%
BB	432	35.97%	753	28.48%
B or below	83	6.91%	188	7.11%
Total	1201	100.00%	2644	100.00%
Panel B: Frequency of Splits with Moody's Ratings				
Aaa	0~	0.00%		
Aa	54	4.50%	170	6.43%
A	176	14.65%	533	20.16%
Baa	286	23.81%	830	31.39%
Ba	281	23.40%	602	22.77%
B or below	404	33.64%	509	19.25%
Total	1201	100.00%	2644	100.00%

* Notch level frequency is distributed with category level splits
~Firms rated Aaa by Moody's are all rated same by S&P

4.4.2 Persistence of Split Ratings

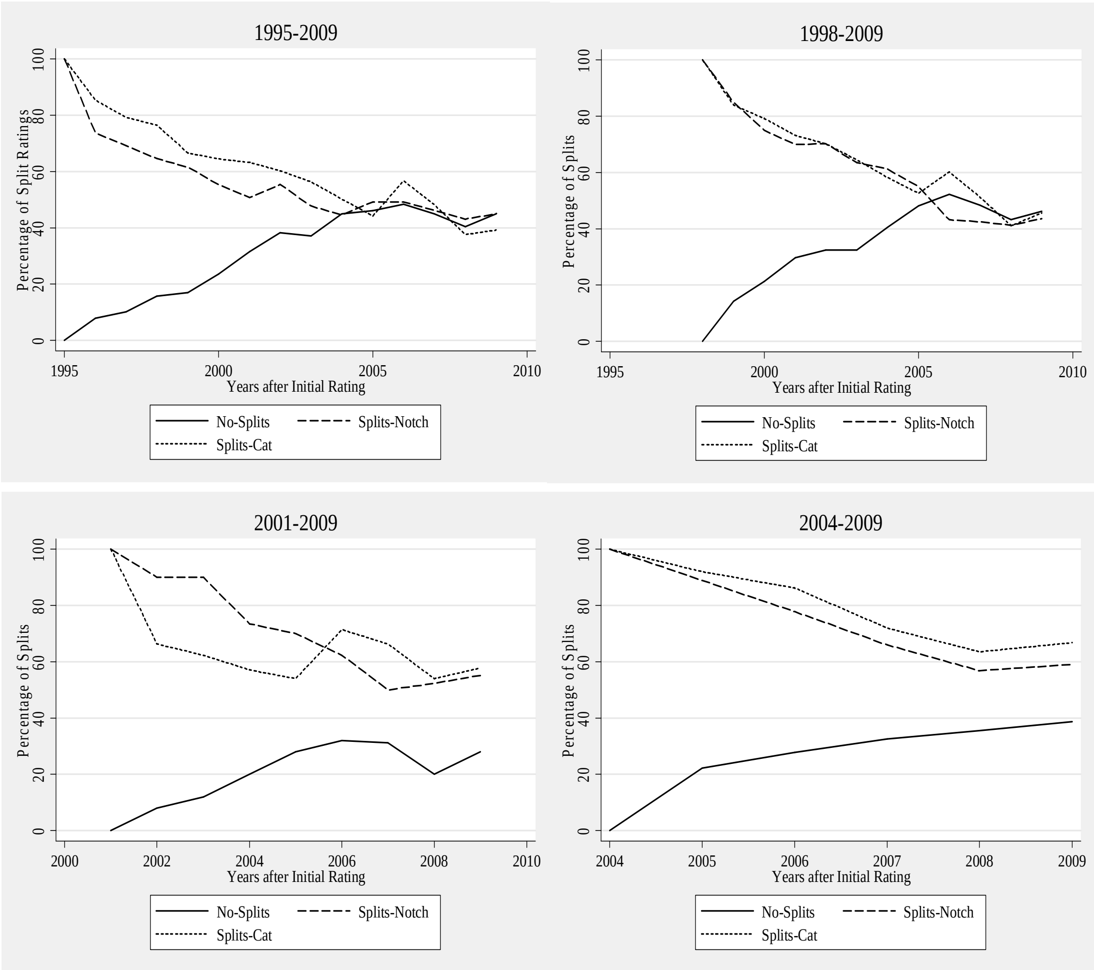
Figure 4.2 presents the graphical presentation of the four sub-samples 1995-2009, 1998-2009, 2001-2009, and 2004-2009. In each sub-sample we have rating transitions of three distinct sets of issuers; non-split firms, splits at the notch level, and splits at the category level. In terms of constructing these graphs, in the first graph 1995-2009, for the initial year 1995, we divide all the firms for which we have fifteen years of rating history into three groups; (i) a first group of issuers where the ratings assigned by the two agencies are congruent in the year 1995, (ii) a second set of firms with rating splits at the notch level in the year 1995, and (iii) final group of issuers with initial ratings designated as splits at the category level in the first year, 1995. Similarly, with the other three graphs, our base year changes to 1998, 2001, and 2004, and we require firms included in the calculation to have a complete ratings history to 2009.

If we look at the four graphs presented in figure 4.2, we observe that the lines for the three set of issuers converge in our initial two samples 1995-2009 and 1998-2009. In these first two samples, containing fifteen and thirteen years of split and non-split rating transitions, more than 40% of the split rated firms at the category level remain splits at same category level. In the first sample from 1995-2009, around 50% of the splits at the notch level still remain splits after fifteen years of rating history. In the second sample, we observe that around 45% of initial splits at the notch level remain splits at the notch level. In both the initial samples, almost 50% of the initial non-split rated firms still have split ratings at the end of our data window in the year 2009. Now, if we look at the last two shorter samples, we observe that the nine years of data from 2001-2009 around 60% of the initial split-rated firms still remain split-rated firms at the end of our sample period. Moreover, in both the last two samples around 30% of initial non-split rated firms are rated splits at the end of the sample period.

In all our samples, even after fifteen years of possible rating transition in some cases, split rated issuers at the beginning of the sample still remain split, and non-split issuers tend to remain non-split rated. Moreover, we do observe some rating changes as well as rating consistency. Morgan (2002) opacity suggests the split credit ratings between the two major agencies are caused by an asset opacity problem, and demonstrates financial firms are more prone to have split ratings due to their asset structure. Livingstone et al. (2007) complement the Morgan (2002) study, and show not only that financial firms are more likely to have split credit ratings, but also that other industrial firms characterized by asset opacity are also likely to have more splits than other firms. They track their split rating bonds transitions and reiterate that after four years of initial issuance, about two thirds of initially split-rated bonds remain split-rated. The reason given in their study is that the asset opacity does not change rapidly, and so split ratings would still remain so for some time in future. Our tracking of split rated firms suggest that even after fifteen years of rating history these splits remain splits in few cases. Moreover in some cases, issuers initially granted non-split ratings are assigned a split rating during our sample period. This shows that asset opacity is unlikely to be the only issue behind split ratings. In fact, there may be fundamental disagreement between the two agencies on some particular issue or issuer based on fundamentals or other information.

Figure 4.2 Rating Convergence

This figure reports the percentage of split rating transitions of three subsamples: 1) initial non-split ratings sample, 2) initial splits ratings at notch level sample, and 3) initial split ratings at category level splits. The data covers fifteen years 1995 through 2009, and the initial year of rating is when a particular issuer is included in the three indices used in the study; S&P 500, S&P 400 and S&P 600. Initial year of rating is not new rating assignment, but inclusion of issuer in the indices.



4.4.3 Bivariate Probit Estimates

The bivariate probit process is applicable to the analysis of a rating splits setting as its use of the two-stage process provides additional insights. In the first stage, we use a vector of explanatory variables X, to determine the probability of having a split rating. In the second stage we determine why one agency places an issuer lower within a split. The vector of X variables used in the study are standard financial information variables as used in previous studies, as well as governance and other related variables which have been found to have explanatory power in relation to credit ratings.

In equation (4.4), y_1 equals 1 if an issuer has a split rating, and y_2 equals 1 if within a split credit rating, S&P rates an issuer lower than Moody's. This study takes into account splits at both the notch and category level. We estimate two separate models for the different dependent variables notch and category level splits, starting with splits at the notch level, and proceeding to examine splits at the category level.

Model Estimates for Splits at Notch Level

Table 4.6 presents the two-stage model estimations results which considers notch and category level splits as the dependent variable in the first stage, and S&P lower rating within a split between S&P and Moody's as the dependent variable in the second stage. The model is based upon 5238 firm-year observations; we have 2644 splits at a notch level. In these 2644 observations, S&P is lower for 715 observations within a split that accounts for 27% of total splits. Columns 3 and 5 present the estimated coefficients for the bivariate probit estimates in both the stages. Column 6 provides the marginal effects for the joint probability of cases where we have split ratings, and S&P lower within a split, as explained in equation (4.12). We also present the Z statistic for the statistical significance of each variable. The highly significant value of correlation ρ (0.978) suggests that unobservable factors that influence the first stage equation also positively influence the second equation reinforcing the validity of our use of bivariate probit estimation method.

Table 4.6 The Bivariate Probit Model-Splits at Notch Level

The coefficient estimates are for the bivariate probit model using splits at Notch Level. The sample period is 1995-2009, and we exclude Financial and Utility firms from our sample of 5238 issuer-year observations. We classify firms as split rated firm at Notch level; when AA+ is different from AA. Coefficient estimates in the second column are for the dependent variable in our first stage bivariate model where y1 equals 1 if the issuer rating has split credit ratings at notch level and 0 when the ratings are congruent between S&P and Moody's. The Fourth column explains coefficient estimates for our second stage bivariate model, where dependent variable y2 equals 1 if the S&P credit rating is lower within a split and zero when Moody's rating is lower in a split Last two columns tells the marginal effects of having a probability of a split when S&P ratings are lower in a split.

	Split Ratings vs. No Splits(y_1=1) Coefficient	Z Statistic	S&P Lower vs Moody's Lower in a split (y_2=1) Coefficient	Z Statistic	Marginal Effects	Z Statistic
Constant	1.320***	7.11	-0.913***	-4.11		
Size Measure (LAssets)	-0.071***	-4.15	-0.005	-0.24	-0.002	-0.24
Market Beta	-0.044	-1.31	-0.015	-0.36	-0.003	-0.36
Coverage Measure	-0.0034*	-1.82	0.003	1.22	0.001	1.22
Leverage Measure	-0.160	-1.11	-0.203	-1.1	-0.044	-1.1
Profitability	-0.752***	-2.8	-0.424	-1.49	-0.091	-1.49
G-Score	-0.019***	-2.77	-0.047***	-5.41	-0.01***	-5.43
% of Ins. Investment	-0.270**	-2.37	0.059	0.41	0.013	0.41
% of Out Directors	-0.513***	-4.52	0.507***	3.44	0.109***	3.44
Ratting shopping	0.205***	5.11	0.103**	2.05	0.022**	2.06
Business cycle	-0.003	-0.27	-0.003	-0.24	-0.001	-0.24
Regulation FD	0.146***	3.36	-0.120**	-2.27	-0.026**	-2.23
ρ	0.978***					
Log likelihood	-5051.60					
Wald $\chi^2(22)$	263.22					
$\chi^2(1)$	1140.64					

Note: *** significant at the 1-percent level
** significant at the 5-percent level
* significant at the 10-percent level

First, we discuss our results based upon first stage probit regressions given in Column 2. Our results suggest that of the five financial information based variables, three measures are statistically significant in ascertaining splits between Moody's and S&P. The three significant measures influencing the probability of having a split rating are the selected size, coverage, and profitability measures. These three measures negatively influence the probability of having a split between the two agencies. The negative sign on these three variables shows that larger issuers with high coverage and profitability ratios are less likely to have split ratings. We do not find any statistically significant impact of leverage or the market beta of an issuer on the likelihood of having a split at notch level. We find our three governance related variables significantly influence the probability of having a split. All the three governance related variables have a negative sign. The negative sign on the G-Score suggests that greater the management control of a firm, the lower the probability of having a split rating between the two agencies. Similarly, a higher percentage of institutional investment and percentage of independent directors on the board reduces the probability of having split ratings.

If we look at the other three variables, we find that rating shopping and regulation FD both positively impact the probability of having a split. In our first stage regressions, we do not find any statistically significant impact of the business cycle proxy. This shows that recessions and expansions have no impact on the probability of split credit ratings. This finding is consistent with Santos (2006) who argues that split credit ratings are not affected by the business cycle, although the cost of issuing bonds over a recession period is higher, as compared to an expansion period. On the other hand, an issuer possessing three or more ratings by different agencies has a higher probability of having a rating split. The Regulation FD dummy also has a significant and positive sign, showing that introduction of regulation FD has increased the probability of having a split.

Column 4 provides the coefficient estimates for our second stage bivariate probit estimates. This stage informs us about the likelihood of S&P placing issuers lower compared to Moody's within a split. We do not find any significance attached to any of the five financial information based variables. The first stage probit regressions using splits at the notch level, shows a higher likelihood of having splits for a smaller firm (in terms of its assets) and one with low coverage and profitability ratios. But, these three significant factors in the first stage probit determining splits do not influence S&P placing firms lower within a split. This suggests that larger firms with favourable coverage and profitability ratios face similar standards by the two agencies. However, when a firm has characteristics of a smaller firm with low coverage and profitability ratios, then Moody's has more stringent standards and rates firms lower compared to S&P, resulting in a split.

In the second stage probit regressions, we find that while a higher G-Score has a negative impact on the probability of split credit ratings, it also decreases the probability of having S&P lower in a split. A similar signs on G-Score in both first and second stage probit regressions show higher G-Score reduces likelihood of a split, and also it reduces likelihood of S&P lower within a split. The G-Score is an equal weighted index that measures restrictions placed upon shareholder rights, and a higher G-Score evidences higher management control of a firm and weaker shareholder rights. The statistical significance of G-Score suggests two agencies differ on the assessment of shareholders rights in a firm. A similar sign in both stages suggests S&P places firms having more management control (higher G-Score) in a higher credit rating compared to Moody's, resulting in a split. Similarly, the higher percentage of outside directors on board increases probability of having S&P lower within a split. The opposite signs in two stages suggest two rating agencies view board structure differently. This suggests Moody's views independence of the board structure more favourably for rating actions, and places firms having more independent directors in a higher rating category compared to S&P. Our third governance variable the percentage of institutional investment is only significant in the first stage, but insignificant in the second stage. Bhojraj and Sengupta (2003) suggest that firms with a greater proportion of outside directors on the board provide better monitoring of management actions. Ashbough et al. (2006) suggests it is difficult or costly to remove management that is acting opportunistically from firms having higher management control vis-à-vis shareholders. On the contrary Klein (1998) finds no relationship of firm performance with the board composition. Our results suggest Moody's is more focused towards the changes in governance structure and places firms with higher board independence and higher institutional investment in a higher rating compared to S&P, resulting in a split.

Now we consider the three additional factors, where we include variables to capture a possible subjective element involved in the likelihood of splits. In the case of our first selected proxy to demonstrate rating shopping behaviour, we find in both stages a positive and significant sign on our rating shopping dummy. Becker and Milbourn (2011) find evidence of rating inflation by Moody's and S&P in response to increased competition and entrance of the third largest rating agency, Fitch. The addition of dummy to demonstrate rating shopping behaviour increases the likelihood of having splits, however it increases probability of S&P lower in a split as well. Similar signs in both the stages suggest rating shopping behaviour increases the likelihood of splits, but we cannot be sure of which agency evidences rating inflation, as in the second stage it increases likelihood of S&P being lower in a split. Our second statistically significant sign is observed on the regulation FD dummy. In the first stage, we find a positive sign and in the second stage we find a negative impact of regulation FD on the probability of S&P placing lower within a split. This can be interpreted as the introduction of regulation FD increasing the probability of having split ratings, resulting in S&P having higher ratings compared to Moody's. Jorion et al. (2005) study the relationship between the information content of credit rating downgrades and upgrades in the post- and the pre-regulation periods, and they find that the informational effects of CRAs is greater in the post-regulation period. Our results suggest after the introduction of regulation FD, Moody's has become more stringent. The introduction of regulation FD has increased the role and use of CRA information in the market. Our results suggest the higher use of CRA information by the market participants have further increased reputational concerns for Moody's compared to S&P. These results suggest Moody's is more cautious on over-predicting PD compared to S&P, as any incorrect prediction may harm its reputation more compared to pre-regulation period. However, this is only visible in case of Moody's, and S&P seems to follow lax standards compared to Moody's in post-regulation period.

Last two columns of table 6 present the marginal effects of the joint probability of having splits and S&P having a lower rating in a split. Our results suggest that the change in percentage of outside directors on board has highest impact on the discrete change of the dependent variable from 0 to 1. We also find that the three other statistically significant factors in determining S&P lower, within a split have statistically significant marginal effects.

Model Estimates for Splits at Category Level

Table 4.7 presents the results for the bivariate model estimates based upon splits at a category level only. Out of our total 5238 firm-year observations, 1201 splits are at a category level, of these S&P is lower in 260(21.64%) observations. Our results suggest that of the five financial information based variables, we have four significant variables. The only variable which is not statistically meaningful is the market beta variable. Here, we have a negative sign on all the four significant financial information based variables. This negative sign suggests that when a firm is larger, has more coverage, leverage and is more profitable, it has less probability of having a split. The first three signs on financial ratios are as we expect, as two agencies may have congruent ratings when a firm is large, and has favourable coverage and profitability ratios. However a negative sign on the leverage ratio suggests that having higher leverage ratio reduces the likelihood of a split. This suggests the two rating agencies have similar standards on leveraged firms, suggesting deteriorating credit quality for more highly leveraged firms. However, the improvement in leverage ratios is taken differently by the two agencies. In terms of the three governance related measures, we find that two measures, G-Score and the percentage of outside directors on the board, both have statistically significant coefficients, while the percentage of institutional investment is insignificant. Both the G-Score and percentage of outside directors on the board, have a negative sign. This suggests that the higher the extent of management control, and the greater the percentage of independent directors on the board, both decrease the probability of having a split at category level. Considering the other three variables, we find only Regulation FD has a statistically meaningful result, its positive sign suggesting that the introduction of this particular regulation has increases the probability of having a split category level rating.

When examining the second stage bivariate probit estimates, six out of the eleven variables have statistically meaningful results. In terms of financial variables, we find that the coefficient on the log of total assets, has a highly significant negative value. This shows that larger firms have a reduced probability of having S&P rating an issuer lower than Moody's. Similarly, we find a negative coefficient on the leverage measure. This suggests that higher leverage reduces the probability of having S&P lower than Moody's within a split. We also see profitability has a negative coefficient, suggesting that greater profitability reduces the probability of S&P providing a lower rating than Moody's.

Table 4.7 The Bivariate Probit Model-Splits at Category Level

The coefficient estimates are for the bivariate probit model using splits at the category level. The sample period is 1995-2009, and we exclude Financial and Utility firms from our sample of 5238 issuer-year observations. We classify firms as split rated firm at category level; when AA+ is different from A, but not from AA- and AA. Coefficient estimates in the second column are for the dependent variable in our first stage bivariate model where y1 equals 1 if the issuer rating has split credit ratings at notch level and 0 when the ratings are congruent between S&P and Moody's. Fourth column explains coefficient estimates for our second stage bivariate model, where dependent variable y2 equals 1 if the S&P credit rating is lower within a split and zero when Moody's rating is lower in a split Last two columns tells the marginal effects of having a probability of a split when S&P ratings are lower in a split. .

	Split Ratings vs. No Splits(y_1=1) Coefficient	Z Statistic	S&P Lower vs Moody's Lower in a split (y_2=1) Coefficient	Z Statistic	Marginal Effects	Z Statistic
Constant	1.209***	5.9	-0.622**	-2.17		
Size Measure (LogAssets)	-0.111 ***	-5.74	-0.105***	-3.82	-0.01***	-3.82
Market Beta	0.021	0.56	0.064	1.24	0.006	1.24
Coverage Measure	-0.006**	-2.51	0.001	0.27	0.001	0.27
Leverage Measure	-0.475***	-3.01	-0.726***	-3.09	-0.068***	-3.1
Profitability	-0.719***	-2.68	-1.118***	-3.15	-0.105***	-3.15
G-Score	-0.018**	-2.34	-0.072***	-6.29	-0.007***	-6.45
%Ins. Investment	-0.022	-0.17	0.439**	2.15	0.041	
% of Out. Directors	-1.069***	-8.52	0.576***	2.81	0.054	
Rating shopping	0.064	1.43	0.110	1.63	0.0103	1.63
Business Cycle	-0.007	-0.66	-0.003	-0.19	-0.003	
Regulation FD	0.122**	2.47	-0.104	-1.4	-0.011	-1.37
ρ	0.980***					
Log likelihood	-3270.62					
Wald $\chi^2(22)$	359.19					
$\chi^2(1)$	861.442					

Note: *** significant at the 1-percentlevel
** significant at the 5-percent level
* significant at the 10-percent level

In the second stage regressions, we have statistically significant coefficient estimates on all the three governance related variables. The percentage of institutional investment is not significant in the first stage regressions; however we have a positive sign in the second stage, suggesting that a higher percentage of institutional investment increases the probability of having a S&P rating lower than Moody's. These results suggest Moody's looks favourably on the credit quality of an issuer in terms of the percentage of institutional investment, whereas this measure causes splits between the two agencies, but also keeps S&P lower within a split. Similarly, in the case of the percentage of independent directors on the board, we have a negative sign in the first stage regression and positive sign in the second stage probit regressions. This reveals that within a split, having a higher percentage of independent directors' increases the probability of having S&P lower within a rating. Finally, we also have a negative sign on the G-Score variable indicating greater management controls vis-à-vis shareholders rights reduce the probability of having a split, as well as having S&P lower within a split. These three signs on the governance related variables suggest Moody's assigns more weight and monitors closely the changes in governance indicators, as improvements in governance related variables is increasing likelihood of S&P placing issuers lower in a split.

In the final two columns of table 4.7, we present estimates of the marginal effects of the joint probability of having splits and S&P having lower rating in a split. Our results suggest that the percentage change in profitability ratios have the highest impact on discrete changes in the dependent variable. We also find the changes in size, leverage and the G-score all play significant role in the joint probability of having a split and having S&P lower within a split.

Comparison of the Two Models

The first model shown in table 4.6 defines rating splits between S&P and Moody's at notch as well as at category level. The second model shown in table 4.7 considers splits at a category level only, and notch level differences between the two agencies are considered to be congruent ratings. In this section, we discuss the differences in our results between the two models formulations.

In the first stage, where we have split rating as the dependent variable, we find differences and similarities between the two models. In both the models, we find similar signs and statistical significance on the following variables: size, coverage, profitability, G-Score, the percentage of outside directors and the Regulation FD. These similarities between the two estimated models suggest that all these variables have a role to play in determining split ratings. These first stage results suggest all the six variables play a role in both splits at the notch and category level. In both the models, the market beta and our business cycle proxy do not exhibit any statistical significance in determining the likelihood of either, notch or category splits. Market beta captures an equities risk relative to the whole index, and the business cycle dummy maps the relative impact of ups and downs in the economy on the split ratings. These results suggest rating agencies do not frequently change ratings on the basis of current market movements; instead as per their policy, they rate through the cycle taking into consideration all the stages of a business cycle. The findings also suggest the splits arise due to factors specific to a firm, rather than factors influencing the whole economy and the markets. Another interpretation of these results can also be that both the agencies react to business cycles and market reaction in the same fashion resulting in congruent rating actions.

The two models also evidence some differences. The first difference is in relation to the leverage measure. In the initial model, which includes a higher number of split observations due to the inclusion of notch level differences, the leverage measure was insignificant. In the second model, we find a statistically significant negative sign on our leverage measure, suggesting that at the category level the two rating agencies place more importance to leverage ratios. This shows that leverage measure is a key component in financial assessment of a firm, and changes in leverage measure produce category level splits. Similarly, the percentage of institutional investment is insignificant in our second model, suggesting the percentage of institutional investment does not play any role in explaining category level differences. The third difference is between the significance of the rating shopping behaviour dummy. In our first model, we find rating shopping dummy significant. This suggests that rating shopping behaviour of issuer firms is not influential in obtaining category level ratings, but that contain issuers may be able to derive notch level differences from such activity.

If we compare the results of the second stage regressions between the two models, we find further differences between our results. Two of our Governance related variables namely the G-Score and the percentage of outside directors on board have equivalent signs in both the models. Moreover, size, leverage, profitability and the percentage of institutional investment measures are significant in the category model, and insignificant in notch level model. The rating shopping dummy and dummy on regulation FD are significant in our notch model, but insignificant in the category model. Recall, our second stage regressions estimates within splits, the probability of having S&P rating lower than Moody's. Our differences in two models show, the two agencies have different preferences while allocating a split at notch and category level.

4.4.4 Further Discussion and Robustness

In the study, we use economic growth as our proxy to show the stages of the business cycle. We use the annual percentage growth in GDP as a proxy for the stage of the business cycle. As a robustness check, following Santos (2006) we also use the NBER defined business cycle peaks and troughs. We use a recession dummy to relate the incidence of split ratings with the business cycle, and find results that are qualitatively similar to those of our GDP proxy presented above. Similarly in terms of financial information variables, we computed multiple financial ratios based on previous studies shown to have relevance to credit ratings. In our study we preset results based upon using coverage ratio equal to (EBITDA (earnings before interest) to XINT (interest charge)). We find no difference if we replace the first coverage ratio with (OIADP (operating income after depreciation) to XINT (interest charge)) ratio. Our results also remain if we replace the leverage ratio we use in the study (DLTT (total long-term debt) to total assets) with (DLTT+DLC (long-term debt total + debt in current liabilities) to Total Assets). Similarly our results hold when replacing our selected profitability measure, (EBITDA (earnings before interest) to sales) with (net income (loss) to total assets). As these ratios capture same aspects of firm characteristics such as leverage, coverage and profitability, we only include one ratio each to demonstrate firm leverage, coverage and profitability.

This is the first study to use Bivariate Probit regressions in a credit ratings setting. As a robustness check, we also estimate different probit regressions. The bivariate probit model utilizes maximum likelihood estimation (MLE) method to allow error terms to be correlated across equations. The parameter ρ_{u1u2} estimates the correlation between the error terms of the bivariate probit equations 4.4 for each model using splits at notch and category level. If the MLE estimate of the correlation coefficient ρ_{u1u2} is significant, then the bivariate model is efficient (Meng and Schmidt (1985)). In both our models, the estimated correlation coefficient between two equations is 0.978 and 0.980, and significant at 1% level. This shows that our method of using a Bivariate Model is more efficient. The highly significant values of χ^2 of 1140.64 and

861.442 in both the estimated model also validate our use of Bivariate Probit model. However, we also estimate separate probit models for comparison purposes. For each splits at the notch level, and at the category level, we estimate separate probit regressions for the following dependent variables: namely, (i) standard probit regressions for split as a dependent variable, (ii) standard probit model for S&P lower within a split as a dependent variable, and (iii) Moody's lower within a split as a dependent variable. In terms of the economic significance and signs of each variable in relation to the appropriate dependent variable, we find no differences compared the results we present. We also attach our estimated probit model regressions for both notch level differences and category level differences as appendix VII and appendix VIII to this thesis.

4.5 Concluding Remarks

This study investigates the rationale behind split credit ratings between S&P and Moody's. The study uses index constituent issuer firms from S&P 500, S&P 400 and S&P 600 indices which have ratings from both the major agencies S&P and Moody's. Our sample consists of 5238 firm-year observations over a fifteen year sample of data, 1995 through 2009. We track rating history for our sub-sample of issuers having splits at the notch level, splits at the category level and having no-splits at the beginning of each sub-sample period. We estimate two separate Bivariate Probit regression models. In the first model we use splits defined as differences between the two rating agencies at either the notch or category level as a dependent variable. The second model uses splits defined as a difference at the category level only. As the second stage in both the models, we use S&P ratings lower within split ratings as a dependent variable.

Our results suggest that over 40% of initial splits at category level remain split rated even after fifteen years of rating transitions. Livingstone et al. (2008) explains the persistence of split ratings as a qualitative difference between the split and non-split rated bonds. Our findings at the notch level splits using Bivariate probit regressions indicate that in terms of financial variables, larger firms having favourable coverage and profitability measures are less likely to have a split. However, smaller firms with unfavourable coverage and profitability measures, are rated lower by Moody's compared to S&P, suggesting Moody's is more conservative when rating such firms. In terms of governance related variables, S&P and Moody's both keep ratings high for a firm having higher management control vis-à-vis shareholder rights. However, Moody's places a higher value on the board independence and places firms with higher board independence to higher rating categories S&P. Our three other variables suggest that business cycle variables do not play any significant role in explaining splits between the two agencies. However, rating shopping and the introduction of regulation FD increase the likelihood of having splits. The introduction of regulation FD has increased the likelihood of Moody's placing a firm lower in a split, suggesting they pay more attention to reputational concerns following higher dependence on ratings by the markets.

For category level splits, we find that leverage level differences along with other financial variables also play a role in category level splits. We find that rating shopping behaviour and the percentage of institutional investment does not play any significant role on the probability of having splits at the category level. We conclude that larger firms, with more favourable coverage and profitability ratios are less likely to have splits at the category level. We find that when the leverage level is high, the two agencies have similar standards in terms of penalizing high leverage. However, when the leverage level is favourable, the agencies reveal different standards as to the implication of such favourable levels of leverage on the credit quality of an issuer, resulting in a split at category level. We also find that the introduction of regulation FD increases the probability of having a split at the category level.

In terms of comparison of notch and category level splits, we conclude that of our selected variables, size, coverage and profitability all play a role in explaining both types of splits. However, leverage differences have a more profound impact on category level splits. In terms of governance related variables, we conclude that the G-Score and the percentage of outside directors play a role in both types of splits. The percentage of institutional investment is not significant when it comes to category level differences. We also conclude that rating shopping behaviour within issuer firms plays an important role in notch level differences; however, it does not have any impact on category level splits. In accordance with Santos (2006), we also find that the business cycle plays no significant role in determining the probability of splits of any type.

The study contributes to the literature on split credit ratings in several dimensions. First, we do not limit our findings to the factors determining likelihood of splits, but we further contribute to identifying factors that determine whether one agency has lower ratings than the other in a split. Ederington (1986) concludes that the split ratings are caused by random errors. Morgan (2002) finds split ratings are due to asset opacity, and Livingstone et al. (2007) shows there is a degree of persistence in split ratings. Morgan (2002) finds the split ratings are lopsided, with Moody's consistently on the downside. These findings suggest split ratings are caused by fundamental differences on issuer credit profile, and we isolate factors that appear to influence the conservative and optimistic behaviour of these two agencies. Second, we also contribute in terms of extending the domain of the range of variables used to explain credit ratings, as we do not limit our factors only to financial variables, but we include variables capturing governance and other subjective elements in ratings to observe their impact on the likelihood of splits. Finally, we also contribute in terms of analyzing differences between notch level and a category level split. A further extension to this study would be to find issuer level preferences in selecting a rating agency on the basis of these factors. Whether there is any evidence that firms have a preference for a particular agency on the basis of the factor differences we identify remain an area for future research.

Chapter 5

Summary of Findings and Suggestions for Future Research

The thesis examines the properties of the ratings allocated by the two major CRAs namely Moody’s and S&P. Following our introduction, this thesis examined the agency’s loss function preferences in chapter 2, credit rating determinants in the chapter 3, and the likelihood of splits in relation to factors determining the allocation of split ratings across the two agencies in the chapter 4.

In chapter 2, we estimate the loss function preferences across both Moody’s and S&P. To the best of our knowledge, this is the first empirical study that applies “loss function” estimation method in a credit rating setting. We estimate loss function parameters following the Elliott et al. (2005) methodology. Using a sample of nineteen years starting 1991 through 2009, we define our rating judgment error as the difference between the MPD_t and the RPD_t. We use the Merton (1974) model to estimate MPD_t following the Vassalou and Xing (2004) methodology.

Our empirical results suggest that CRA loss function preferences, rationality and incentives appear to vary across the two major rating agencies. Our results suggest a systematic asymmetry of loss function preferences in Moody’s, whereas we find evidence of symmetric loss function estimates for S&P. However, across both the agencies, we find a similar asymmetry in the utility and financial sectors. In Moody’s, apart from the financial and utility sectors, we find strong evidence of conservative preferences. In S&P, we do not observe any consistency in the estimated loss function alpha parameters. We observe pessimistic as well as optimistic preferences, although the median value of the sample, excluding financial and utility sectors, suggests symmetric preferences. Across both the agencies, we find that the financial and utility sectors appear to exhibit more optimistic preferences. Our results suggest, as a result of the under-prediction of the RPD_t, the bulk of estimated alphas are lower than one half, implying an optimistic preference structure.

In terms of incentives, Moody’s conservative approach can be associated with the use of its ratings by regulatory agencies. For example, Beaver et al. (2006) document that regulatory and contractual needs force NRSRO firms to be more conservative. We supplement Beaver et al.'s (2006) findings in three directions: First, we estimate loss function preferences for the first time, second, we provide evidence Moody's does not exhibit conservatism across every sector, and third, we provide evidence that the conservative preferences associated with Moody's cannot be generalized across all NRSRO firms, as we document more symmetric preferences from S&P. We conclude that one general criticism of CRAs, namely that they possess incentives to inflate ratings, is not observed in industry sectors other than financial and utility sectors. However, the under-prediction of PD for financial and utility sector firms needs attention from CRAs and regulatory authorities.

The second essay (Chapter 3) examined the importance of various financial and other variables in explaining the credit ratings issued by the two major rating agencies S&P and Moody's. We use index constituent issuer firms from the S&P500, S&P 400 and S&P 600 indices, where all firms in our sample have received ratings from both the agencies. The final sample utilises 5192 firm-year observations from 1995 through 2009. Using ordered probit estimation methods, we examine the prediction success matrix to determine the goodness-of-fit of the estimated models. Overall, we find that all the incorporated financial variables are highly significant factors in determining the assignment of credit ratings. Our size measure has the most pronounced effect on the credit ratings for both the agencies. Interestingly, we also find certain difference between the two rating agencies in terms of the impact of our selected financial variables. A firm's market beta has more effect on the credit ratings allocated by S&P as compared to Moody's, while the coverage ratio is revealed to have more importance in determining Moody's ratings than for S&P. In both the agencies, we find that changes in leverage and profitability play the least important role in the allocation of credit ratings.

We also determine the effects of governance variables on firms' credit ratings by using a firm's initial financial characteristics as control variables. Specifically, we find that firm credit ratings are: (1) positively associated with a higher G-Score, indicating that firms with greater degrees of management as opposed to shareholder control have higher credit ratings; (2) positively related to the percentage of institutional investment; and (3) positively related to overall board independence. In the case of S&P, changes in governance variables have the least impact of any variables in the allocation of credit ratings. By adding three governance variables, we find a slight improvement of around two percent in the predictive success of our model for both the agencies. Finally, we add three additional variables, which can be associated with the general criticisms directed towards rating agencies and also attempt to capture subjectivity elements involved in the rating process. We conclude that firms that exhibit rating shopping behaviour tend to get lower credit ratings as compared to other firms. This suggests the two major rating agencies may be concerned with their reputation. We also find that a variable capturing the introduction of Regulation FD has a highly significant negative impact, suggesting more stringent standards from the two agencies have been adopted in the post-Regulation FD period. This has two aspects; first, after the introduction of Regulation FD, market participants may have placed an increasing reliance upon rating agencies information and ratings, which in turn has made the rating agencies more vigilant and stringent. We also find a positive and significant sign on our proxy for the stage of the business cycle. This suggests that rating agencies are more stringent during times of economic turmoil and slowdown.

An important finding of this study (Chapter 3) is that incorporating these three additional variables significantly improves our ability to predict the rating category of firms allocated to the higher categories. This suggests that subjective elements play an important role in discriminating between high rating category issuers, where incorporating only fundamental factors fails to correctly predict higher-rated firms.

The third essay (chapter 4) investigated the rationale behind split credit ratings between S&P and Moody's. The study again uses index constituent issuer firms from the S&P 500, S&P 400 and S&P 600 indices which have been given ratings by both the major agencies, S&P and Moody's. Our sample consists of 5238 firm-year observations over a fifteen year sample of data, 1995 through 2009. We estimate two separate Bivariate Probit regression models. In the first model we use splits defined as differences between the two rating agencies at either the notch or category level as a dependent variable. The second model uses splits defined as a difference at the category level only. In both models, at the second stage we use S&P ratings lower within split ratings as our dependent variable.

Our results suggest that over 40% of initial splits at category level remain split rated even after fifteen years of rating transitions. Our findings in terms of notch level splits using bivariate probit regressions indicate that larger firms having favourable coverage and profitability measures are less likely to have a split. However, smaller firms with unfavourable coverage and profitability measures are rated lower by Moody's as compared to S&P, suggesting Moody's is more conservative when rating such firms. In terms of governance related variables, S&P and Moody's both keep ratings high for a firm having higher management control vis-à-vis shareholder rights. However, Moody's places a higher value on the board independence and allocates firms with higher board independence into higher rating categories than S&P. Our three other variables suggest that business cycle variables do not play any significant role in explaining splits between the two agencies. However, rating shopping and the introduction of regulation FD increase the likelihood of having splits. The introduction of regulation FD has increased the likelihood of Moody's placing a firm lower in a split, suggesting they pay more attention to reputational concerns.

For category level splits, we find that leverage level differences, along with other financial variables, also play a role in category level splits. We find that rating shopping behaviour and the percentage of institutional investment does not play any significant role on the probability of having splits at the category level. In terms of comparison of notch and category level splits, we conclude that of our selected variables, size, coverage and profitability all play a role in explaining both types of splits. However, leverage differences have a more profound impact on category level splits. In terms of governance related variables, we conclude that the G-Score and the percentage of outside directors play a role in both types of splits. The percentage of institutional investment is not significant when it comes to category level differences. We also conclude that rating shopping behaviour within issuer firms plays an important role in notch level differences; however, it does not appear to have any impact on category level splits.

In this thesis, we examine and identify several areas of current literature where we observed gaps, and we attempt to address some of those gaps and puzzles. However, our findings and approach suggest further research areas need developing. In our first essay (chapter 2), we examined the loss function preference structure of CRAs, comparing market and RPD_t. Our results are based upon ex-post default rates of CRAs. Further work can be undertaken to find more appropriate measures of RPD_t (ex ante) and the more accurately capture a representative measure of market sentiment. In the second essay (chapter 3), we provide evidence of the importance of using subjective elements to capture the determination of credit ratings after controlling for financial and governance variables. This suggests another area of further research, as the development and incorporation of further proxies to demonstrate conflict of interest and criticism may further improve the prediction of overall ratings. In our third essay (chapter 4), we study the reasons behind split credit ratings. A further extension to this study would be whether their exists issuer level preferences for selecting a rating agency on the basis of these factors. Whether there is any evidence that firms have a preference for a particular agency on the basis of the factor differences we identify remains an area for future research.

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Appendices

Appendix I Moody's - Long term Credit Rating Scale

Aaa

Obligations are judged to be of the best quality. 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. 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 sometime 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.

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.

Note: Ratings from ‘Aa’ to ‘CCC’ may be modified by the addition of a plus 1,2 or 3 to show relative standing within the major rating categories.

Source: Rating Symbols and Definitions available at: http://www.moodys.com

Appendix II S&P - 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.

BB+

Considered highest speculative grade by market participants

BB

Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions

B

More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments

CCC

Currently vulnerable and dependent on favourable business, financial and economic conditions to meet financial commitments

CC

Currently highly vulnerable

C

A bankruptcy petition has been filed or similar action taken, but payments of financial commitments are continued

D

Payments default on financial commitments

Note: 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. Ratings above BB+ are considered to be Investment Grade, and BB+ and less are speculative grade.

Source: Credit Rating Essentials available at http://www.standardandpoors.com/ratings

Appendix III Rating Comparison

S&P	Moody's	Fitch
AAA	Aaa	AAA
AA+	Aa1	AA+
AA	Aa2	AA
AA-	Aa3	AA-
A+	A1	A+
A	A2	A
A-	A3	A-
BBB+	Baa1	BBB+
BBB	Baa2	BBB
BBB-	Baa3	BBB-
BB+	Ba1	BB+
BB	Ba2	BB
BB-	Ba3	BB-
B+	B1	B+
B	B2	B
B-	B3	B-
CCC+	Caa1	CCC+
CCC	Caa2	CCC
CCC-	Caa3	CCC-
CC	Ca	CC
C	C	C
D		D

Source: BIS Website http://www.bis.org/

Appendix IV Moody's Annual Corporate Default Rates by Alphanumeric Rating

Year	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3
1983	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.6	0.0	9.1	17.9		53.3	
1984	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.1	1.2	1.6	0.0	5.9	17.6	3.0			
1985	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.6	2.9	4.4	7.1	11.7		0.0	
1986	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.4	0.9	1.2	3.4	7.8	15.2	15.4		28.6	
1987	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.8	0.9	3.0	4.2	7.7	10.2		22.2	
1988	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.6	4.2	6.9	11.0		23.5	
1989	0.0	0.0	0.0	1.4	0.0	0.0	0.0	0.0	0.8	1.0	0.8	1.9	4.8	5.6	9.2	18.3		27.3	
1990	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.7	2.8	3.5	7.8	21.7	29.9		58.3	0.00
1991	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.0	0.0	1.1	0.0	9.1	3.5	11.0	28.0		48.0	0.00
1992	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	1.0	1.5	26.6		31.6	0.00
1993	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0	0.8	2.5	3.3	10.1		25.0	0.00
1994	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	1.9	3.6	8.8		7.0	0.00
1995	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.8	4.4	5.9	2.0		2.7	0.00
1996	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.2	0.0	3.3	0.0	15.0	0.00
1997	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	1.2	7.0	0.0	13.6	0.00
1998	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	1.9	1.2	2.1	5.4	4.9	5.8	12.0	26.66
1999	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.5	0.6	2.5	2.6	5.4	8.1	11.2	21.8	21.42
2000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	1.0	0.5	0.6	1.0	3.1	4.9	11.3	11.2	29.5	20.69
2001	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.3	0.3	0.0	0.0	1.4	2.8	3.2	10.4	18.0	25.8	33.3	47.61
2002	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.8	0.7	1.9	2.4	0.6	1.1	2.2	4.7	7.6	16.0	25.8	33.76
2003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.7	1.5	0.4	2.4	4.4	8.6	21.9	31.81
2004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0	0.6	2.4	8.0	9.2	15.09
2005	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3	0.0	0.0	0.0	0.0	0.6	2.5	3.1	6.3	21.05
2006	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.8	0.6	2.2	2.3	6.7	18.18
2007	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.2	8.4	14.81
2008	0.0	0.0	0.0	1.7	1.2	0.0	0.0	0.3	0.8	0.3	0.0	0.0	2.7	1.8	0.8	3.2	7.8	19.0	32.87
2009	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.9	0.7	0.7	2.4	0.6	4.0	3.7	8.5	8.6	17.1	38.9	57.14
Mean	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.1	0.4	0.7	0.6	2.0	2.8	6.1	10.2	8.5	22.7	17.05

* Data in percent Source: Corporate Default and Recovery Rate (Moodys Annual Publication)

Appendix V S&P Global Corporate Default Rates by Rating Modifier

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C
1983	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.33	2.17	0.00	1.59	1.22	9.80	4.76	6.67
1984	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.40	0.00	0.00	1.64	1.49	2.13	3.51	7.69	25.00
1985	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.64	1.49	1.33	2.59	13.11	8.00	15.38
1986	0.00	0.00	0.00	0.00	0.00	0.00	0.78	0.00	0.78	0.00	1.82	1.18	1.12	4.65	12.16	16.67	23.08
1987	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.83	1.31	5.95	6.82	12.28
1988	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.34	1.98	4.50	9.80	20.37
1989	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.91	0.78	0.00	0.00	0.00	2.00	0.43	7.80	4.88	33.33
1990	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.77	0.00	1.10	2.78	3.06	4.50	4.87	12.26	22.58	31.25
1991	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.83	0.74	0.00	3.70	1.12	1.05	8.72	16.25	32.43	33.87
1992	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.72	14.93	20.80	30.19
1993	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.92	0.00	1.30	5.88	4.17	13.33
1994	0.00	0.00	0.00	0.00	0.45	0.00	0.00	0.00	0.00	0.00	0.00	0.86	0.00	1.83	6.58	3.23	16.67
1995	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.63	0.00	1.55	1.11	2.76	8.00	7.69	28.00
1996	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.86	0.65	0.55	2.33	3.74	3.92	4.17
1997	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.34	0.00	0.00	0.00	0.41	0.72	5.19	14.58	12.00
1998	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.27	1.05	1.30	1.06	0.72	2.57	7.47	9.46	42.86
1999	0.00	0.00	0.00	0.36	0.00	0.24	0.27	0.00	0.28	0.31	0.54	1.33	0.90	4.19	10.55	15.45	32.35
2000	0.00	0.00	0.00	0.00	0.00	0.24	0.56	0.00	0.26	0.88	0.00	0.80	2.30	5.59	10.66	11.50	34.12
2001	0.00	0.00	0.00	0.00	0.57	0.49	0.00	0.24	0.48	0.27	0.49	1.19	6.00	5.94	15.74	23.31	44.55
2002	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.12	0.65	1.32	1.50	1.74	4.62	3.69	9.63	19.53	44.12
2003	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.53	0.48	0.94	0.28	1.69	5.21	9.23	33.13
2004	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.65	0.77	0.46	2.68	2.82	15.33
2005	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.36	0.00	0.25	0.78	2.60	2.98	8.94
2006	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.00	0.48	0.54	0.79	1.57	12.38
2007	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	0.23	0.19	0.00	0.88	15.09
2008	0.00	0.00	0.44	0.41	0.31	0.21	0.58	0.19	0.59	0.71	1.14	0.63	0.64	2.97	3.31	7.41	26.26
2009	0.00	0.00	0.00	0.00	0.29	0.39	0.00	0.40	0.18	1.09	0.00	1.02	0.91	5.48	9.96	17.16	48.42
Mean	0.00	0.00	0.02	0.03	0.06	0.07	0.08	0.17	0.27	0.32	0.66	0.90	1.50	2.55	7.37	10.23	23.61

Data in Percent. Sources: Annual Default Tables S&P

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

S.No	Sector	Moody's True Alpha			Moody's a=0.2	Moody's a=0.5	Moody's a=0.8	S&P True Alpha			S&P a=0.2	S&P a=0.5	S&P a=0.8
		a	SD	J	J	J	J	a	SD	J	J	J	J
1	AAP Consumer Discretionary	0.79	0.14	0.58	4.99	2.67	0.58	0.79	0.14	0.58	4.99	2.67	0.58
2	AM	0.71	0.11	1.98	8.95	2.76	3.28	0.22	0.10	0.00	0.05	5.56	11.86
3	BID	0.94	0.10	2.00	14.90	10.94	2.05	0.31	0.11	1.02	1.69	3.88	10.38
4	BTH	0.92	0.07	1.01	12.45	10.31	3.29	0.58	0.13	1.06	6.48	1.70	2.64
5	BWA	0.78	0.11	1.32	8.90	3.57	1.49	0.78	0.11	1.32	8.90	3.57	1.49
6	BWS	0.84	0.09	0.93	11.43	7.85	1.21	0.84	0.09	0.93	11.43	7.84	1.21
7	BYD	0.71	0.12	1.65	9.45	4.78	1.79	0.47	0.13	0.28	3.50	0.31	4.65
8	BYI	0.78	0.10	0.04	11.86	5.57	0.09	0.61	0.11	0.27	7.50	1.09	2.47
9	CBRL	0.54	0.13	0.84	5.60	1.02	3.43	0.54	0.13	0.84	5.60	1.02	3.43
10	CHUX	0.85	0.09	1.00	11.86	8.09	1.33	0.77	0.11	1.00	10.34	5.51	1.00
11	CSTR	0.83	0.11	1.75	8.16	6.37	1.96	0.83	0.11	1.75	8.16	6.37	1.96
12	EAT	0.44	0.12	1.08	4.86	1.06	6.16	0.50	0.12	1.06	4.86	1.06	6.16
13	FL	0.80	0.10	0.59	11.91	6.31	0.59	0.57	0.12	2.10	8.63	2.89	3.84
14	GCO	0.81	0.10	0.12	10.39	5.52	0.13	0.78	0.11	1.18	9.06	4.97	1.17
15	ICON	0.54	0.13	0.84	4.82	0.95	3.47	0.03	0.05	4.81	6.85	5.28	7.68
16	ISCA	0.50	0.14	1.05	4.51	1.05	3.28	0.50	0.14	1.15	3.28	1.15	4.64
17	JAS	0.94	0.06	1.31	11.91	8.16	1.48	0.94	0.06	2.43	10.40	5.71	1.63
18	KBH	0.82	0.09	1.26	13.31	8.71	1.39	0.02	0.04	5.84	3.54	2.90	8.96
19	LAMR	0.76	0.13	0.76	6.97	3.86	0.77	0.74	0.13	1.88	8.00	4.99	1.80
20	LIZ	0.77	0.11	1.02	10.39	5.57	1.02	0.26	0.13	8.00	6.04	1.29	3.46
21	LKQX	0.93	0.11	0.65	4.46	2.70	0.33	0.92	0.11	0.65	4.46	2.70	0.32
22	MDC	0.32	0.11	0.68	1.57	3.09	9.18	0.50	0.12	0.48	4.81	0.48	4.97
23	MHK	0.32	0.12	2.33	3.98	2.17	7.04	0.32	0.12	2.33	3.98	2.17	7.04
24	MTH	0.75	0.11	2.53	8.35	5.94	2.42	0.12	0.08	5.54	5.99	4.61	6.36
25	NVR	0.91	0.07	1.73	13.56	10.77	4.14	0.56	0.12	0.39	6.15	0.62	3.58
26	OMX	0.77	0.11	1.01	10.32	5.55	1.01	0.46	0.13	1.06	4.64	0.98	4.70
27	OXM	0.70	0.12	1.12	9.01	3.74	1.52	0.77	0.11	1.02	10.36	5.57	1.02
28	PBY	0.54	0.13	0.37	4.69	0.44	3.40	0.38	0.13	1.01	2.36	1.98	6.45
29	PERY	0.69	0.12	0.98	7.68	3.13	1.48	0.65	0.12	2.33	7.41	3.99	2.74
30	PETM	0.87	0.09	2.76	10.15	9.31	3.67	0.87	0.09	2.76	10.15	9.31	3.67
31	PNK	0.69	0.12	0.96	8.14	3.34	1.46	0.69	0.12	0.96	8.14	3.34	1.46
32	PVH	0.39	0.12	0.03	2.36	0.91	7.48	0.39	0.11	0.03	2.36	0.91	7.48
33	RCII	0.36	0.12	2.13	3.30	2.09	6.12	0.53	0.13	0.29	4.66	0.35	3.40

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

		Moody's						S&P					
S.No	Sector	True Alpha			a=0.2	a=0.5	a=0.8	True Alpha			a=0.2	a=0.5	a=0.8
34	RYL	0.06	0.05	4.50	3.19	4.44	10.41	0.05	0.05	2.36	1.53	8.19	13.38
35	SAH	0.55	0.13	2.51	5.85	2.90	3.71	0.53	0.13	0.26	4.65	0.31	3.43
36	SCHL	0.73	0.11	1.02	9.40	3.23	1.63	0.39	0.12	1.51	2.95	2.67	8.17
37	SMP	0.69	0.12	0.93	7.45	2.08	1.95	0.69	0.12	0.93	7.45	2.08	1.95
38	SPF	0.47	0.13	0.10	3.35	0.16	4.64	0.47	0.13	0.10	3.35	0.16	4.64
39	TOL	0.50	0.12	1.70	6.75	1.70	4.93	0.37	0.11	1.49	3.95	1.75	7.54
40	TUP	0.50	0.14	0.48	3.49	0.48	3.22	0.20	0.12	1.01	1.00	3.24	7.42
41	ZQK	0.85	0.09	1.02	11.36	8.07	1.38	0.46	0.13	1.44	4.98	1.30	4.73
	Consumer Staples												
1	ACV	0.50	0.12	1.08	6.18	1.08	4.86	0.24	0.10	1.24	1.72	3.89	10.39
2	AOI	0.25	0.11	0.47	0.68	3.50	8.90	0.12	0.08	0.35	1.10	8.16	11.91
3	CHD	0.50	0.12	1.06	4.86	1.06	6.16	0.76	0.10	1.21	10.39	3.88	1.70
4	CPO	0.30	0.12	2.01	2.10	4.75	9.05	0.39	0.13	2.40	2.94	3.63	8.18
5	FLO	0.44	0.12	1.05	3.66	1.53	7.52	0.44	0.12	1.05	3.66	1.53	7.52
6	GAP	0.70	0.12	1.28	7.49	2.66	1.76	0.04	0.05	3.67	3.90	4.56	8.95
7	NAFC	0.75	0.11	2.41	7.57	3.59	2.47	0.39	0.13	0.85	2.33	1.70	6.28
8	NTY	0.50	0.12	0.24	4.79	0.24	4.83	0.50	0.12	0.23	4.79	0.23	4.83
9	SFD	0.56	0.12	0.84	6.89	1.26	3.63	0.32	0.11	0.62	1.90	2.29	8.92
10	UVV	0.57	0.12	1.50	6.18	1.38	5.34	0.10	0.07	0.26	1.69	10.93	14.90
	Energy												
1	ACI	0.73	0.10	2.58	8.96	2.92	3.66	0.65	0.11	2.29	7.56	2.14	4.78
2	CKH	0.85	0.09	1.04	11.11	8.03	1.41	0.74	0.11	0.10	8.89	3.30	0.43
3	CRK	0.67	0.11	0.09	8.91	2.07	1.37	0.57	0.12	1.63	6.42	1.98	3.82
4	FST	0.75	0.10	1.03	11.88	5.78	1.12	0.31	0.11	1.15	2.59	2.47	8.93
5	FTO	0.32	0.11	0.65	1.56	2.98	9.10	0.88	0.08	1.03	13.38	8.20	1.25
6	KWK	0.77	0.14	1.72	5.77	4.34	1.64	0.77	0.14	1.72	5.77	4.34	1.64
7	NFX	0.71	0.11	0.97	9.80	4.15	1.31	0.57	0.12	0.98	6.90	1.51	3.13
8	OSG	0.37	0.11	1.61	4.14	1.81	7.54	0.38	0.11	0.74	3.09	1.34	7.51
9	PDE	0.23	0.10	3.53	3.74	3.50	9.00	0.03	0.04	5.84	6.76	4.79	9.08
10	PETD	0.76	0.11	2.76	8.67	6.57	2.62	0.76	0.11	2.76	8.66	6.57	2.62
11	PQ	0.74	0.11	0.04	8.89	3.29	0.36	0.73	0.11	0.04	8.89	3.29	0.36
12	PXP	0.08	0.09	2.74	2.62	2.05	4.52	0.06	0.08	0.50	0.86	5.46	7.45
13	SFY	0.77	0.11	0.97	9.03	4.69	0.99	0.77	0.11	0.97	9.03	4.69	0.99
14	SGY	0.92	0.07	1.01	13.44	11.28	3.79	0.92	0.07	1.00	13.44	11.28	3.79
15	SM	0.47	0.13	0.10	3.35	0.16	4.64	0.47	0.13	0.10	3.35	0.16	4.64

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

		Moody's						S&P					
S.No	Sector	True Alpha			a=0.2	a=0.5	a=0.8	True Alpha			a=0.2	a=0.5	a=0.8
16	SPN	0.97	0.04	5.87	7.09	2.89	5.24	0.37	0.12	0.49	2.06	1.37	6.99
17	SUG	0.16	0.09	1.62	1.92	8.32	12.13	0.14	0.08	0.57	1.06	8.95	13.44
	Financials												
1	AF	0.43	0.12	1.93	5.41	1.71	6.21	0.20	0.09	0.80	0.77	5.72	11.87
2	AFG	0.50	0.12	1.07	4.86	1.07	6.17	0.31	0.11	1.03	1.70	3.89	10.39
3	AMB	0.43	0.13	0.01	2.46	0.29	5.05	0.50	0.13	0.09	3.73	0.09	3.72
4	ASBC	0.39	0.12	0.23	2.50	1.04	7.49	0.50	0.00	3.00	1.57	8.19	13.38
5	BRE	0.44	0.12	1.05	3.66	1.53	7.52	0.44	0.12	1.08	4.86	1.06	6.16
6	BXS	0.19	0.09	1.03	1.08	8.16	13.40	0.50	0.12	1.07	4.86	1.07	6.18
7	CFR	0.22	0.10	0.03	0.08	5.57	11.86	0.29	0.11	1.99	3.29	2.76	8.95
8	CLI	0.39	0.12	0.29	2.42	1.22	7.53	0.39	0.11	0.00	2.35	0.89	7.48
9	CLP	0.46	0.13	1.14	4.77	1.05	4.71	0.46	0.13	1.14	4.77	1.05	4.71
10	CPT	0.46	0.13	0.97	4.54	0.91	4.70	0.46	0.13	0.97	4.54	0.91	4.70
11	CYN	0.39	0.12	4.42	7.84	3.24	6.35	0.17	0.00	7.00	6.53	3.20	7.64
12	DFG	0.31	0.12	1.06	2.11	2.13	7.45	0.46	0.13	0.64	3.92	0.63	4.68
13	EQY	0.13	0.11	0.91	1.39	5.95	7.57	0.13	0.11	0.91	1.39	5.95	7.57
14	FAF	0.44	0.12	1.21	4.32	1.20	6.17	0.44	0.12	1.21	4.32	1.20	6.17
15	FMBI	0.39	0.13	0.69	2.90	1.04	6.03	0.63	0.01	2.99	1.21	5.61	10.39
16	FRT	0.31	0.11	1.15	2.59	2.47	8.93	0.31	0.11	1.15	2.59	2.47	8.93
17	HCC	0.29	0.11	0.91	1.28	3.93	9.05	0.29	0.11	0.91	1.28	3.93	9.05
18	HIW	0.41	0.13	1.21	3.83	1.15	5.11	0.41	0.13	1.21	3.83	1.15	5.11
19	HMN	0.44	0.12	0.25	3.63	0.43	6.11	0.28	0.11	0.00	0.53	3.56	10.37
20	HPT	0.29	0.08	7.00	5.87	1.67	2.98	0.29	0.08	7.00	5.87	1.67	2.98
21	HR	0.39	0.13	0.87	3.17	1.14	6.04	0.31	0.12	0.81	2.00	2.01	7.44
22	IPCC	0.50	0.14	0.23	3.20	0.23	3.27	0.50	0.14	0.23	3.20	0.23	3.27
23	JEF	0.33	0.11	0.00	1.33	2.00	8.91	0.33	0.11	0.00	1.33	2.00	8.91
24	JLL	0.45	0.15	0.31	2.33	0.44	3.67	0.45	0.15	0.31	2.33	0.44	3.67
25	LRY	0.37	0.11	1.51	4.07	1.75	7.54	0.43	0.12	1.46	5.30	1.35	6.18
26	MCY	0.11	0.07	0.07	1.42	10.90	14.90	0.11	0.07	0.07	1.42	10.90	14.90
27	MSCI	0.22	0.15	0.37	0.46	2.08	4.94	0.83	0.13	0.97	6.20	4.39	1.09
28	NAVG	0.62	0.13	1.23	6.05	1.35	3.57	0.69	0.12	1.00	8.82	3.50	1.47
29	NHP	0.20	0.00	2.00	4.67	11.17	14.91	0.20	0.00	2.00	4.67	11.17	14.91
30	NNN	0.54	0.13	1.05	6.03	1.27	3.46	0.46	0.13	1.10	4.72	1.01	4.71
31	NYB	0.25	0.10	0.95	1.27	3.95	10.39	0.16	0.09	0.08	0.23	8.02	13.37
32	O	0.54	0.13	0.84	4.69	0.79	4.28	0.54	0.13	0.84	4.69	0.79	4.28

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

		Moody's						S&P					
S.No	Sector	True Alpha			a=0.2	a=0.5	a=0.8	True Alpha			a=0.2	a=0.5	a=0.8
33	OHI	0.67	0.11	3.13	10.77	5.94	3.28	0.21	0.10	2.14	2.23	4.15	10.40
34	ONB	0.16	0.09	0.95	0.73	5.52	10.39	0.31	0.12	1.01	2.18	2.08	7.45
35	ORI	0.50	0.12	1.06	4.86	1.06	6.16	0.06	0.06	1.00	5.51	14.24	16.45
36	PCH	0.50	0.12	1.08	4.86	1.08	6.19	0.31	0.11	1.05	1.71	3.93	10.42
37	PLFE	0.74	0.11	0.14	8.90	3.41	0.42	0.60	0.13	0.01	6.00	0.61	2.15
38	PPS	0.54	0.13	1.06	6.05	1.29	3.46	0.38	0.13	1.12	3.46	1.29	6.04
39	REG	0.47	0.13	0.22	3.37	0.29	4.67	0.47	0.13	0.22	3.37	0.29	4.67
40	SIGI	0.70	0.12	1.19	7.45	2.15	2.37	0.38	0.13	1.05	2.36	2.15	7.46
41	SIVB	0.10	0.07	1.46	1.08	8.13	13.38	0.26	0.10	0.67	1.20	3.76	10.38
42	SKT	0.31	0.12	0.95	1.45	3.40	8.63	0.38	0.13	1.36	3.71	1.42	6.05
43	SNH	0.22	0.14	0.02	0.04	2.78	5.93	0.44	0.17	0.37	1.99	0.42	3.07
44	SUSQ	0.37	0.13	1.74	3.89	1.65	6.07	0.29	0.12	1.68	2.65	2.33	7.46
45	THG	0.45	0.14	1.09	4.16	0.99	4.18	0.64	0.13	1.20	5.52	1.35	2.98
46	TRH	0.63	0.11	1.10	7.52	1.53	3.66	0.19	0.09	1.01	1.06	8.12	13.37
47	UDR	0.44	0.12	1.01	4.78	1.01	6.15	0.37	0.11	1.02	3.56	1.48	7.52
48	UTR	0.28	0.11	0.03	0.55	3.57	10.37	0.28	0.11	0.03	0.55	3.57	10.37
49	WBS	0.22	0.10	0.21	0.25	5.60	11.86	0.22	0.10	0.21	0.25	5.60	11.86
50	WDR	0.74	0.14	0.89	6.18	3.38	0.92	0.50	0.16	0.67	3.18	0.67	2.71
51	WTNY	0.15	0.09	1.05	0.77	5.53	10.39	0.46	0.13	0.99	4.58	0.92	4.70
52	ZNT	0.62	0.13	1.04	7.45	2.14	2.36	0.62	0.13	1.12	6.04	1.29	3.46
	Health Care												
1	AGP	0.72	0.13	1.53	6.11	3.08	1.62	0.50	0.14	0.38	3.24	0.38	3.24
2	BEC	0.50	0.12	1.06	4.86	1.06	6.16	0.44	0.12	1.05	3.66	1.53	7.52
3	BIO	0.68	0.11	0.75	8.97	2.74	1.65	0.68	0.11	0.75	8.97	2.74	1.65
4	CNMD	0.92	0.07	0.89	11.91	8.12	1.09	0.89	0.08	1.77	10.39	5.60	1.09
5	COO	0.92	0.07	0.94	12.58	10.86	3.47	0.68	0.12	0.70	7.91	2.87	1.35
6	CRL	0.54	0.14	0.48	4.14	0.51	3.00	0.46	0.14	0.77	2.92	0.93	4.39
7	CYH	0.85	0.12	0.95	7.45	5.54	1.82	0.85	0.12	0.95	7.45	5.54	1.82
8	HGR	0.12	0.09	1.52	1.55	5.82	10.40	0.23	0.11	1.02	1.20	3.60	8.90
9	HMA	0.92	0.06	1.86	15.46	13.58	5.06	0.11	0.07	0.02	1.35	10.89	14.90
10	HNT	0.23	0.10	1.62	1.89	4.04	10.39	0.24	0.10	3.13	3.66	3.20	8.98
11	HOLX	0.62	0.11	0.72	7.68	1.83	2.52	0.62	0.11	0.49	7.60	1.51	2.46
12	HRC	0.31	0.11	1.02	1.70	3.87	10.31	0.13	0.08	0.88	0.76	8.08	13.37
13	HS	0.13	0.08	1.00	0.82	8.09	13.37	0.13	0.08	1.00	0.82	8.09	13.37
14	HWAY	0.54	0.13	1.50	4.96	1.65	3.59	0.33	0.12	0.23	1.21	1.86	7.44

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

				Moody's						S&P			
S.No	Sector		True Alpha		a=0.2	a=0.5	a=0.8		True Alpha		a=0.2	a=0.5	a=0.8
15	KCI	0.50	0.25	1.33	1.22	1.33	2.49	0.50	0.25	1.33	1.22	1.33	2.49
16	KNDL	0.65	0.14	0.46	5.07	1.43	1.28	0.65	0.14	0.46	5.07	1.43	1.28
17	LPNT	0.97	0.06	2.89	4.48	1.53	1.93	0.57	0.17	0.77	3.82	1.07	1.87
18	MTD	0.68	0.11	0.43	8.98	2.55	1.49	0.67	0.11	0.35	8.96	2.45	1.46
19	OCR	0.61	0.12	0.01	7.48	0.90	2.35	0.44	0.12	0.21	3.55	0.44	6.12
20	OMI	0.79	0.10	0.48	11.87	5.68	0.50	0.61	0.11	0.13	7.49	0.99	2.40
21	PSSI	0.88	0.08	0.25	11.91	8.09	0.76	0.75	0.11	0.62	8.90	3.44	0.94
22	PSYS	0.99	0.03	1.99	3.01	1.28	1.85	0.76	0.17	1.08	4.21	2.83	1.03
23	RSCR	0.67	0.12	0.14	7.43	1.77	1.18	0.86	0.09	2.58	10.96	9.37	3.22
24	VRX	0.93	0.06	0.94	15.65	13.83	5.10	0.80	0.09	0.80	12.50	7.46	0.81
25	VTIV	0.50	0.18	2.29	3.52	2.29	2.41	0.50	0.18	2.29	3.52	2.29	2.41
26	WCG	0.60	0.16	0.00	4.00	0.40	1.43	0.60	0.15	0.00	4.00	0.40	1.43
	Industrials												
1	AAI	0.92	0.07	0.81	13.01	10.53	3.25	0.84	0.09	0.57	11.45	7.19	0.75
2	ABFS	0.43	0.13	3.95	4.91	3.60	5.05	0.43	0.13	3.95	4.91	3.60	5.05
3	AGCO	0.42	0.12	1.52	4.45	1.39	5.66	0.42	0.12	1.52	4.45	1.39	5.66
4	AIR	0.58	0.13	0.37	5.11	0.68	2.54	0.35	0.13	0.45	1.55	1.50	6.48
5	ALK	0.89	0.07	1.25	13.37	8.10	0.91	0.76	0.10	1.27	10.39	3.90	1.74
6	AME	0.43	0.12	2.19	3.85	3.01	8.97	0.58	0.12	2.36	6.24	2.01	6.24
7	ASGN	0.45	0.13	2.20	4.56	2.01	4.82	0.55	0.13	2.28	5.92	2.65	3.66
8	ATK	0.81	0.09	0.98	13.26	8.02	1.02	0.81	0.09	0.98	13.26	8.02	1.02
9	ATU	0.85	0.09	1.09	10.39	5.53	0.78	0.46	0.13	0.97	4.43	0.90	4.70
10	BCO	0.50	0.12	1.16	4.87	1.16	6.29	0.56	0.12	0.97	6.15	0.98	4.70
11	BEAV	0.78	0.10	0.11	11.87	5.66	0.15	0.50	0.12	0.42	4.82	0.42	4.85
12	CLH	0.42	0.12	2.97	4.21	3.29	6.58	0.42	0.12	2.97	4.21	3.29	6.58
13	CNW	0.36	0.11	1.77	4.15	1.90	7.55	0.36	0.11	1.78	4.16	1.91	7.55
14	CR	0.57	0.12	1.92	6.21	1.69	5.80	0.38	0.11	0.82	2.53	2.08	8.01
15	CSL	0.50	0.12	1.10	4.87	1.10	6.21	0.44	0.12	1.09	3.66	1.58	7.58
16	CXW	0.59	0.14	0.31	4.57	0.66	2.01	0.70	0.13	0.92	6.04	2.38	1.28
17	DLX	0.69	0.11	1.00	10.32	3.83	1.69	0.25	0.10	0.96	1.49	3.83	10.38
18	ESL	0.71	0.12	1.57	7.47	2.45	2.21	0.71	0.12	1.57	7.47	2.45	2.21
19	FCN	0.50	0.13	1.86	5.52	1.86	3.89	0.71	0.12	0.00	7.90	2.57	0.49
20	GEO	1.00	0.01	1.99	11.91	8.18	1.74	1.00	0.01	1.99	11.91	8.18	1.74
21	GY	0.70	0.12	1.38	7.45	2.23	2.43	0.70	0.12	1.38	7.45	2.23	2.43
22	HSC	0.13	0.08	1.00	0.82	8.09	13.37	0.13	0.08	1.00	0.82	8.09	13.37

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

		Moody's						S&P					
S.No	Sector	True Alpha			a=0.2	a=0.5	a=0.8	True Alpha			a=0.2	a=0.5	a=0.8
23	IEX	0.56	0.12	0.82	7.09	1.24	3.62	0.68	0.11	0.60	8.95	2.53	1.60
24	IFSIA	0.54	0.13	0.88	4.81	0.98	3.48	0.54	0.13	1.28	4.76	1.26	3.75
25	JBLU	0.99	0.05	1.97	3.01	1.29	1.84	0.20	0.01	2.00	2.34	1.54	3.02
26	JOYG	0.32	0.17	1.16	1.28	2.46	5.07	0.67	0.17	1.03	4.89	2.22	1.23
27	KAMN	1.00	0.01	2.99	10.39	5.65	1.46	0.63	0.12	1.87	6.07	1.70	4.18
28	KEX	0.50	0.12	0.07	4.78	0.07	4.78	0.50	0.12	0.07	4.78	0.07	4.78
29	KMT	0.34	0.11	2.82	5.17	2.38	7.58	0.39	0.11	0.20	2.40	1.12	7.52
30	KSU	0.78	0.10	0.13	11.86	5.59	0.17	0.50	0.12	0.52	5.22	0.52	4.81
31	LII	0.67	0.17	1.01	3.51	1.01	1.90	0.67	0.17	1.01	3.51	1.01	1.90
32	MLHR	0.31	0.11	1.02	2.46	2.43	8.93	0.24	0.10	1.25	1.73	3.89	10.39
33	NCS	0.47	0.13	0.01	3.34	0.08	4.63	0.33	0.12	0.02	1.12	1.68	7.43
34	ORB	0.55	0.13	2.04	5.88	2.39	3.62	0.55	0.13	2.03	5.87	2.38	3.62
35	OSK	0.81	0.09	0.96	13.06	7.95	1.00	0.01	0.02	5.96	3.13	2.70	8.95
36	PNR	0.44	0.12	1.06	3.66	1.53	6.97	0.44	0.12	1.06	3.66	1.52	6.97
37	ROCK	0.86	0.09	1.20	11.88	8.65	1.73	0.54	0.13	0.99	5.76	1.20	3.45
38	SPW	0.99	0.02	4.94	10.40	4.19	2.68	0.44	0.12	0.39	3.57	0.67	6.21
39	TEX	0.44	0.12	0.27	3.59	0.46	6.12	0.44	0.12	0.69	3.70	0.86	6.16
40	TKR	0.37	0.11	1.06	3.61	1.51	7.52	0.18	0.09	1.20	1.03	5.75	11.87
41	TNB	0.22	0.10	1.77	1.72	7.52	12.92	0.29	0.11	1.88	2.09	5.56	11.57
42	TTC	0.62	0.13	1.15	6.05	1.31	3.50	0.62	0.13	1.15	6.05	1.30	3.50
43	TRN	0.44	0.12	1.05	4.83	1.04	6.16	0.25	0.10	1.13	1.63	3.86	10.38
44	URS	0.57	0.12	1.59	6.47	1.98	3.80	0.57	0.12	1.59	6.47	1.98	3.80
45	VMI	0.73	0.10	0.43	10.38	3.69	0.97	0.73	0.10	0.43	10.38	3.69	0.97
46	WAB	0.73	0.12	0.95	6.99	2.86	1.17	0.73	0.12	0.95	6.99	2.86	1.17
47	WTS	0.65	0.12	2.33	6.09	1.92	4.54	0.45	0.13	2.06	3.61	2.47	7.25
	Information Technology												
1	ACXM	0.99	0.03	1.79	14.90	10.95	2.17	0.77	0.10	1.68	10.39	3.99	2.01
2	ARW	0.50	0.12	1.25	4.88	1.25	6.27	0.17	0.09	1.42	1.62	9.19	13.79
3	AVT	0.43	0.12	2.33	3.88	3.20	9.15	0.21	0.10	0.26	0.28	5.75	11.87
4	AXE	0.71	0.12	1.62	7.46	2.29	2.71	0.71	0.12	1.62	7.46	2.29	2.71
5	CIEN	0.45	0.15	0.27	2.37	0.34	3.60	0.55	0.15	0.16	3.62	0.27	2.30
6	CTV	0.78	0.13	1.03	7.90	4.61	1.01	0.44	0.12	1.09	3.66	1.58	7.58
7	CVG	0.50	0.16	1.14	4.08	1.14	2.76	0.50	0.16	1.09	4.02	1.09	2.75
8	EQIX	0.69	0.16	1.42	3.70	2.15	1.47	0.69	0.16	1.42	3.70	2.16	1.47
9	FCS	0.68	0.16	0.43	4.49	1.40	0.85	0.68	0.16	0.42	4.49	1.40	0.85

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

		Moody's						S&P					
S.No	Sector	True Alpha			a=0.2	a=0.5	a=0.8	True Alpha			a=0.2	a=0.5	a=0.8
10	IM	0.50	0.14	1.65	4.40	1.65	3.35	0.62	0.14	1.87	5.95	2.95	2.35
11	IRF	0.67	0.11	0.10	8.91	2.06	1.38	0.76	0.10	1.20	10.40	4.11	1.43
12	ITRI	0.54	0.13	0.54	4.72	0.62	3.43	0.54	0.13	0.54	4.72	0.62	3.43
13	JDAS	0.54	0.13	0.54	4.72	0.62	3.43	0.46	0.14	0.47	2.88	0.58	4.20
14	KLIC	0.76	0.11	2.75	10.20	7.11	2.61	0.02	0.03	6.98	7.34	3.36	4.95
15	MINI	0.84	0.13	1.02	4.95	2.25	0.90	0.84	0.13	1.02	4.95	2.25	0.90
16	NCR	0.89	0.09	3.63	5.98	2.10	2.79	0.89	0.09	3.62	5.98	2.10	2.79
17	ROVI	0.44	0.15	1.35	2.76	1.31	3.70	0.18	0.12	0.02	0.05	4.46	7.92
18	TTMI	0.93	0.07	1.09	12.34	11.02	4.19	0.78	0.11	1.28	9.43	5.80	1.25
19	VSH	0.33	0.11	0.20	1.44	2.14	8.92	0.33	0.11	0.20	1.44	2.14	8.92
	Materials												
1	ALB	0.59	0.13	1.11	5.10	1.08	3.81	0.58	0.13	1.11	5.10	1.08	3.81
2	ASH	0.50	0.12	1.06	6.16	1.06	4.86	0.18	0.10	3.00	1.06	8.12	13.37
3	CBT	0.21	0.10	2.00	1.95	8.09	13.14	0.21	0.10	2.00	1.95	8.08	13.14
4	CENX	0.85	0.11	0.43	8.01	5.31	0.63	0.85	0.11	0.43	8.01	5.31	0.63
5	CMC	0.44	0.12	1.06	4.85	1.05	6.16	0.24	0.10	1.17	1.67	3.87	10.39
6	CRS	0.32	0.11	0.50	1.50	2.74	9.05	0.25	0.10	3.05	3.83	3.03	8.97
7	CYT	0.98	0.04	8.02	3.46	1.25	5.99	0.98	0.04	8.02	3.46	1.25	5.99
8	GEF	0.64	0.13	1.15	6.99	2.51	1.92	0.73	0.12	1.17	8.51	4.30	1.25
9	HW	0.80	0.13	1.68	6.05	4.72	1.68	0.64	0.15	1.38	4.50	2.26	1.78
10	LZ	0.36	0.11	2.11	4.64	2.05	7.56	0.36	0.11	2.11	4.64	2.05	7.56
11	MLM	0.50	0.13	1.17	3.82	1.17	5.22	0.50	0.13	1.17	3.82	1.17	5.22
12	NEU	0.22	0.10	0.05	0.10	5.59	11.86	0.22	0.10	0.19	0.22	5.69	11.87
13	NP	0.84	0.12	0.85	6.49	4.82	1.04	0.56	0.17	0.62	3.44	0.86	1.85
14	OLN	0.21	0.10	2.07	2.02	8.26	13.38	0.35	0.11	2.13	2.89	4.25	10.41
15	OMG	1.00	0.01	2.99	10.40	5.77	2.08	0.46	0.13	1.91	5.26	1.70	4.77
16	PKG	0.67	0.16	0.01	4.46	1.01	0.67	0.44	0.17	0.46	1.83	0.64	3.22
17	POL	0.92	0.07	1.00	11.91	8.14	1.25	0.68	0.12	0.55	7.54	2.43	1.31
18	RKT	0.27	0.11	0.00	0.33	3.27	8.89	0.20	0.10	0.05	0.05	5.44	10.39
19	RPM	0.50	0.12	2.57	5.02	2.57	7.93	0.50	0.12	2.57	5.02	2.57	7.93
20	RS	0.42	0.13	1.13	3.82	1.09	5.10	0.41	0.13	1.13	3.82	1.09	5.10
21	SLGN	1.00	0.01	3.00	7.19	8.44	9.71	0.92	0.00	3.00	5.38	4.23	6.53
22	SMG	0.50	0.12	0.71	5.55	0.71	4.83	0.50	0.12	0.71	5.55	0.71	4.83
23	SON	0.59	0.12	3.15	6.28	2.54	6.97	0.26	0.10	0.61	0.89	4.15	10.41
24	STLD	0.99	0.02	1.89	2.21	3.21	3.67	0.50	0.14	0.64	3.86	0.64	3.24

Appendix VI Moody's and S&P Estimated Alphas and J-Statistic

		Moody's						S&P					
S.No	Sector	True Alpha			a=0.2	a=0.5	a=0.8	True Alpha			a=0.2	a=0.5	a=0.8
25	TIN	0.27	0.11	2.28	3.11	2.71	8.95	0.04	0.05	1.39	1.93	10.93	14.90
26	TXI	0.69	0.12	1.01	8.85	3.54	1.48	0.69	0.12	1.01	8.85	3.54	1.48
27	VAL	0.63	0.11	1.21	7.53	1.59	3.77	0.31	0.11	1.11	1.73	4.05	10.51
	Telecommunication Services												
1	CBB	0.77	0.10	1.60	10.39	3.97	1.97	0.50	0.12	1.40	4.89	1.40	6.54
2	TDS	0.13	0.08	1.06	1.19	3.02	4.18	0.27	0.11	0.16	0.62	3.70	10.38
	Utilities												
1	ALE	0.94	0.25	5.00	2.68	2.27	7.46	0.94	0.25	5.00	2.68	2.27	7.46
2	ATO	0.50	0.12	1.10	4.87	1.10	6.21	0.25	0.10	1.15	1.65	3.87	10.39
3	AVA	0.46	0.13	0.97	4.37	0.90	4.70	0.25	0.11	0.59	0.90	3.44	8.90
4	AWR	0.31	0.12	1.06	1.50	3.62	8.90	0.23	0.11	1.06	1.05	5.67	10.40
5	BKH	0.37	0.11	1.33	2.66	2.94	9.34	0.37	0.11	1.33	2.66	2.94	9.34
6	CNL	0.44	0.12	1.05	3.66	1.54	7.53	0.31	0.11	1.03	1.70	3.89	10.39
7	CV	0.50	0.16	1.14	4.08	1.14	2.76	0.54	0.13	1.26	4.72	1.16	4.52
8	DPL	0.25	0.10	0.99	1.51	3.83	10.38	0.56	0.12	1.15	6.16	1.12	4.95
9	DYN	0.46	0.14	0.00	2.81	0.08	4.10	0.22	0.12	0.14	0.19	3.82	8.40
10	EE	0.41	0.14	0.23	2.03	0.52	4.54	0.41	0.14	0.23	2.03	0.52	4.54
11	EGN	0.43	0.12	1.78	3.78	2.48	8.46	0.08	0.07	0.58	2.58	11.07	14.91
12	GXP	0.32	0.11	0.75	2.13	2.33	8.93	0.32	0.11	0.75	2.13	2.33	8.93
13	HE	0.27	0.11	0.16	0.62	3.70	10.38	0.33	0.11	0.14	1.39	2.12	8.92
14	IDA	0.33	0.11	0.12	1.39	2.08	8.91	0.20	0.09	0.72	0.72	5.96	11.88
15	LG	0.79	0.11	1.42	8.90	3.59	1.55	0.15	0.09	1.04	1.42	8.23	11.95
16	MDU	0.19	0.09	1.01	1.07	8.12	13.38	0.19	0.09	1.01	1.07	8.12	13.38
17	NVE	0.16	0.09	0.07	0.23	8.05	13.37	0.09	0.07	0.41	2.43	11.21	14.91
18	NWN	0.58	0.13	0.37	5.11	0.68	2.54	0.35	0.13	0.45	1.55	1.50	6.48
19	OGE	0.27	0.10	2.63	2.57	6.79	10.58	0.09	0.07	0.48	2.53	11.14	14.91
20	PNM	0.69	0.11	1.05	10.41	3.93	1.71	0.44	0.12	1.06	4.83	1.04	6.16
21	PNY	0.38	0.13	1.04	2.36	2.14	7.45	0.38	0.13	1.04	2.36	2.14	7.45
22	SWX	0.67	0.12	3.03	6.11	2.21	5.02	0.67	0.12	3.03	6.11	2.21	5.02

Appendix VII Standard Probit Model Estimates -Splits at the Notch Level

The coefficient estimates are for the standard probit model using splits at the notch level. The sample period is 1995-2009, and we exclude financial and utility firms from our sample of 5238 issuer-year observations. We classify firms as split rated firm at the notch level; when AA+ is different A- or AA. Coefficient estimates are for the three estimated standard probit estimates using three distinct dependent variables (i) split as a dependent variable in panel A (ii) S&P lower within a split as a dependent variable in panel B, and (iii) Moody's lower within a split as a dependent variable explained in C.

	Coefficient	Standard Error	Z Statistic	P-Value
Panel A: Estimates for Splits at the notch level as Dependent				
Constant	1.30	0.18	7.09	0.00
Size Measure(LAssets)	-0.07	0.02	-4.28	0.00
Market Beta	-0.05	0.03	-1.36	0.17
Coverage Measure	0.00	0.00	-1.99	0.05
Leverage Measure	-0.14	0.14	-0.96	0.34
Profitability	-0.68	0.26	-2.60	0.01
G-Score	-0.02	0.01	-2.63	0.01
%Institutional Investment	-0.25	0.11	-2.22	0.03
% of Outside Directors	-0.53	0.11	-4.67	0.00
Rating Shopping	0.21	0.04	5.22	0.00
Business Cycle	0.00	0.01	-0.09	0.93
Regulation FD	0.16	0.04	3.71	0.00
Log likelihood	-3564.11			
Pseudo R^2	0.02			
LR $\chi^2(11)$	132.72			
Panel B: Estimates for observations where S&P is lower within a split				
Constant	-1.01	0.22	-4.51	0.00
Size Measure (L Assets)	0.00	0.02	0.22	0.83
Market Beta	-0.01	0.04	-0.33	0.74
Coverage Measure	0.00	0.00	1.52	0.13
Leverage Measure	-0.12	0.18	-0.67	0.51
Profitability	-0.44	0.29	-1.48	0.14
G-Score	-0.05	0.01	-5.40	0.00
%Institutional Investment	0.10	0.14	0.69	0.49
% of Outside Directors	0.50	0.14	3.45	0.00
Rating shopping	0.10	0.05	1.91	0.06
Business Cycle	-0.01	0.01	-0.52	0.61
Regulation FD	-0.16	0.05	-2.99	0.00
Log likelihood	-2057.81			
Pseudo R^2	0.01			
LR $\chi^2(11)$	59.73			

Panel C: Estimates for observations where Moody's is lower within a split

Constant	0.97	0.19	5.14	0.00
Size Measure (LAssets)	-0.08	0.02	-4.62	0.00
Market Beta	-0.04	0.03	-1.17	0.24
Coverage Measure	-0.01	0.00	-3.39	0.00
Leverage Measure	-0.08	0.15	-0.54	0.59
Profitability	-0.41	0.26	-1.61	0.11
G-Score	0.01	0.01	1.20	0.23
%Institutional Investment	-0.32	0.12	-2.73	0.01
% of Outside Directors	-0.85	0.12	-7.27	0.00
Rating shopping	0.17	0.04	4.02	0.00
Business Cycle	0.00	0.01	0.17	0.87
Regulation FD	0.27	0.05	5.92	0.00
Log likelihood	-3344.00			
Pseudo R^2	0.03			
LR $\chi^2(11)$	205.00			

Appendix VIII Standard Probit Model Estimates -Splits at the Category Level

The coefficient estimates are for the standard probit model using splits at the category level. The sample period is 1995-2009, and we exclude financial and utility firms from our sample of 5238 issuer-year observations. We classify firms as split rated firm at the category level; when AA+ is different from A and AAA, but not from A- or AA. Coefficient estimates are for the three estimated standard probit estimates using three distinct dependent variables (i) split as a dependent variable in panel A (ii) S&P lower within a split as a dependent variable in panel B, and (iii) Moody's lower within a split as a dependent variable explained in C.

	Coefficient	Standard Error	Z Statistic	P-Value
Panel A: Estimates for Splits at the category level as Dependent				
Constant	-0.12	0.02	-5.97	0.00
Size Measure (LAssets)	0.01	0.04	0.31	0.76
Market Beta	-0.01	0.00	-2.72	0.01
Coverage Measure	-0.47	0.16	-3.01	0.00
Leverage Measure	-0.71	0.26	-2.67	0.01
Profitability	-0.02	0.01	-2.16	0.03
G-Score	0.02	0.13	0.16	0.87
%Institutional Investment	-1.08	0.13	-8.58	0.00
% of Outside Directors	0.07	0.04	1.60	0.11
Rating shopping	-0.01	0.01	-0.46	0.65
Business Cycle	0.15	0.05	2.99	0.00
Regulation FD	1.20	0.20	5.90	0.00
Log likelihood	-2705.44			
Pseudo R^2	0.04			
LR $chi^2(11)$	229.52			
Panel B: Estimates for observations where S&P is lower within a split				
Constant	-0.75	0.30	-2.48	0.01
Size Measure (Assets)	-0.07	0.03	-2.51	0.01
Market Beta	0.06	0.06	1.07	0.29
Coverage Measure	0.00	0.00	0.64	0.52
Leverage Measure	-0.60	0.25	-2.37	0.02
Profitability	-1.14	0.35	-3.27	0.00
G-Score	-0.08	0.01	-6.65	0.00
%Institutional Investment	0.40	0.20	2.05	0.04
% of Outside Directors	0.57	0.20	2.83	0.01
Rating shopping	0.08	0.07	1.19	0.24
Business Cycle	0.00	0.02	-0.26	0.80
Regulation FD	-0.20	0.07	-2.70	0.01
Log likelihood	-995.90			
Pseudo R^2	0.04			
LR $\chi^2(11)$	76.65			

Panel C: Estimates for observations where Moody's is lower within a split

Constant	0.96	0.22	4.42	0.00
Size Measure (Log Assets)	-0.11	0.02	-5.10	0.00
Market Beta	0.00	0.04	-0.10	0.92
Coverage Measure	-0.01	0.00	-3.66	0.00
Leverage Measure	-0.34	0.17	-2.04	0.04
Profitability	-0.28	0.28	-1.01	0.31
G-Score	0.01	0.01	1.60	0.11
%Institutional Investment	-0.15	0.14	-1.10	0.27
% of Outside Directors	-1.47	0.13	-10.98	0.00
Rating shopping	0.05	0.05	0.95	0.34
Business Cycle	-0.01	0.01	-0.58	0.56
Regulation FD	0.24	0.05	4.64	0.00
Log likelihood	2325.18			
Pseudo R^2	0.06			
LR $\chi^2(11)$	282.37			