Bangor University

DOCTOR OF PHILOSOPHY

The Impact of Split Credit Ratings on U.S. Corporates: Cost of Capital, Capital Structure and Debt Maturity

Nguyen, Anh Quang

Award date:
2020

Awarding institution:
Bangor University

The Impact of Split Credit Ratings on U.S. Corporates: Cost of Capital, Capital Structure and Debt Maturity

By Quang Anh Nguyen

PhD thesis

Bangor Business School

Bangor University

December 2019

Yr wyf drwy hyn yn datgan mai canlyniad fy ymchwil fy hun yw’r thesis hwn, ac eithrio lle nodir yn wahanol. Caiff ffynonellau eraill eu cydnabod gan droednodiadau yn rhoi cyfeiriadau eglur. Nid yw sylwedd y gwaith hwn wedi cael ei dderbyn o’r blaen ar gyfer unrhyw radd, ac nid yw’n cael ei gyflwyno ar yr un pryd mewn ymgeisiaeth am unrhyw radd oni bai ei fod, fel y cytunwyd gan y Brifysgol, am gymwysterau deuol cymeradwy.

I hereby declare that this thesis is the results of my own investigations, except where otherwise stated. All other sources are acknowledged by bibliographic references. This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree unless, as agreed by the University, for approved dual awards.

Abstract

It is common practice for U.S. firms to solicit multiple ratings, normally from the two largest international credit rating agencies (CRAs), namely Moody's and S&P. It is reported that these two CRAs disagree on U.S. firms' ratings for a majority of sampled observations. This thesis investigates the effect of the two major CRAs' disagreements about firms' creditworthiness (split ratings) upon firms' cost of equity capital, debt maturity decisions and capital structure decisions.

The thesis uses an initial dataset comprising all U.S. corporations rated by both Moody's and S&P during the period from 2003 to 2015 (to 2017 for Chapter 3). Various methodologies are employed to address the research questions, namely cross-sectional regression models, Ordinary Least Squares (OLS), the Tobit model, the Generalised Linear Model (GLM) and propensity score matching (PSM).

The first empirical chapter focuses on the impact of split ratings on the cost of equity capital and provides evidence that equity investors recognise the differences between Moody's and S&P's opinions about firms' credit risk and demand premiums for that uncertainty surrounding firms' creditworthiness. Equity investors are more sensitive to adverse selection/information asymmetry problems than are bond investors; thus, split ratings (as a signal of information opaqueness or information asymmetry) induce equity investors to require a higher cost of equity capital for split rated firms than non-split rated firms. In addition, equity investors put more weight on S&P, a more generous CRA, when assessing firms' cost of equity capital. The second empirical chapter examines the impact of split ratings on firms' debt maturity decisions and provides evidence that split rated firms' behaviour regarding debt maturity is different from that of non-split rated firms. Split rated firms seem more concerned about the rollover risk arising from future unfavourable rating changes than the increase in long-term borrowing cost arising from split ratings. Therefore, they are more likely to issue a higher proportion of long-term debt than non-split rated firms. Firms place more emphasis on Moody's ratings, a more conservative CRA, when deciding on debt maturity structure. The third empirical chapter focuses on the impact of split ratings on firms' capital structure and finds evidence that split rated firms rely more on debt financing than equity financing. The results suggest that firms are more concerned about the adverse selection and information asymmetry problems signalled by split ratings than the increased borrowing cost arising from

split ratings. In contrast to the first two empirical chapters, firms do not differentiate between Moody's and S&P when assessing optimal capital structure decisions.

This thesis highlights drawbacks in the current common practice of researchers and regulators to treat the two major CRAs equally. The thesis reports evidence of systematic differences between the two CRAs and their differing credit opinions reveals additional implications that have a significant impact on firms' and investors' behaviour.

Acknowledgements

I would like to thank my supervisors, Professor Owain ap Gwilym and Dr Rasha Alsakka, for all their help and support over the last four years. I have been extremely lucky to have them as my supervisors and their encouragement, patient guidance and advice has been invaluable throughout the PhD.

I would also like to thank all the staff and students who I have met during my time at Bangor Business School without whom, this work would have been all more difficult.

Thanks to family for supporting me and especially to my wife who has been there for me and helped me to succeed.

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Abbreviations

ABS	Asset-Backed Securities
AEGM	Abnormal Earnings Growth Model
ATE	Average Treatment Effect
ATT	Average Treatment Effect for the Treated
BIS	Bank for International Settlements
CAPM	Capital Asset Pricing Model
CCR	Comprehensive credit rating
CI	Capital Intelligence
CRA(s)	Credit rating agency(ies)
ERC	Earnings Response Coefficients
ESMA	European Securities and Markets Authority
Fitch	Fitch Ratings, Ltd
GLM	Generalized Linear Model
ICC	Implied Cost of Capital
JCR	Japan Credit Rating Agency
NN	Nearest Neighbour
NPL(s)	Non-Performing Loan(s)
NRSRO(s)	Nationally Recognized Statistical Rating Organization(s)
OLS	Ordinary Least Square
PSM	Propensity Score Matching
QMLE	Quasi-Maximum Likelihood Estimators
Moody’s	Moody’s Investors Service
R&I	Japan Rating and Investment Information
RIM	Residual Income Model
S&P	Standard and Poor’s Rating Services (currently branded as S&P Global)
SIC	Standard Industrial Classification
SB	Standardised Bias
SEC	U.S. Securities and Exchange Commission

Chapter 1: Introduction

The U.S. sub-prime mortgage crisis in 2007 – 2008 and the European sovereign debt crisis in 2009 – 2013 have attracted considerable attention to credit rating agencies (CRAs). These two crises have raised public and regulatory scrutiny of the quality of CRAs' ratings and raised questions about the effectiveness of their roles in information certification and monitoring. More intrusive regulatory regimes are now in place surrounding the rating industry in the U.S. and Europe. Meanwhile, the crisis episodes triggered new academic research directions and the policy debate is ongoing. This thesis identifies unique research questions which have not previously been investigated in the academic literature.

In the U.S., it is common that issuers solicit multiple ratings from different CRAs. However, CRAs disagree with each other's opinion (referred to as split ratings) about half of the time (Livingston and Zhou, 2010; Livingston et al., 2010). The key aims of this thesis are to investigate the impact of split ratings on issuers' financial decisions and thereby to contribute to the ongoing policy debate. The thesis delivers many insights on corporate financial behaviour that have implications for investors, regulators and CRAs.

Multiple ratings are important to issuers. In fact, in order to maximise their access to capital markets, U.S. firms are required to solicit ratings from the two major CRAs, Moody's Investors Service (Moody's hereafter) and Standard & Poor's (currently branded as S&P Global, S&P hereafter) (Mahlmann, 2009). This raises the question of why issuers need more than one rating if one is enough to provide the intended information certification and monitoring functions. There are three theories about multiple ratings: information production, rating shopping and regulatory certification (see Section 2.2). Under the information production hypothesis, issuers could reduce the uncertainty of their credit quality by seeking additional ratings (Morkoetter and Westerfeld, 2015). Under the rating shopping hypothesis, issuers solicit multiple ratings in order to 'shop' for the most favourable ratings. Under the regulatory certification hypothesis, issuers solicit additional ratings to meet a regulatory requirement (Bongaerts et al., 2012).

While multiple ratings are common, CRAs disagree with each other's opinions about issuers' creditworthiness most of the time (see, for example, Livingston et al., 2010). There are several reasons that split ratings occur (see Section 2.3.2). Split ratings could be caused by random errors. The default risk assessment processes are so difficult and sophisticated that differing opinions could arise randomly in error (Ederington, 1986). Alternatively, split ratings might arise from systematic differences among CRAs. These differences could be driven by different rating methodologies, different determinants used, different weights applied to those determinants, different rating scales or different evaluation processes (Moon and Stotsky, 1993; Pottier and Sommer, 1999; Livingston et al., 2008; 2010). Furthermore, the occurrence of split ratings could be due to issuers' information opaqueness, which could make it difficult for CRAs to evaluate issuers' credit fundamentals (Livingston et al., 2007; Livingston et al., 2010). Home bias and the influence of large shareholders' bias are also potential causes of split ratings, whereby CRAs are more likely to be biased toward issuers that are located in their home region (Yalta and Yalta, 2018) or are invested in by the CRAs' large shareholders (Kedia et al., 2017).

Notwithstanding the potential reasons for split ratings, both multiple ratings and split ratings have a significant impact on bond yields and prices (see Section 2.3.3). Historically, issues with multiple ratings have on average lower yield compared to issues with a single rating at the same rating categories (Hsueh and Kidwell, 1988). However, in the event of split ratings, bond yields of split rated issues are more likely to be higher than their non-split rated peers (Livingston et al., 2010). Furthermore, split rated issues/issuers are more likely to receive further rating actions in the future (Livingston and Zhou, 2008). These suggest that while split ratings deliver additional information to the market, they are more likely to have unfavourable effects upon issuers.

To the best of my knowledge, this is the first study to investigate the impact of split ratings on firms' cost of equity capital and firms' financial decisions on optimal debt levels and optimal debt maturity ratios. The thesis focusses on the different opinions between Moody's and S&P because these two CRAs are the most dominant in the industry (in 2017, Moody's and S&P together control 71.2% of the U.S. corporate rating market and 82.3% of the total rating market (SEC, 2018)).[1] Disagreement between Moody's and S&P over issuers' creditworthiness could present a potential problem for the debt issuers (an information opaqueness problem/information asymmetry between issuers and investors).[2] Thus, split rated firms are more likely to have uncertainty surrounding their true credit ratings than their non-

[1] The vast majority of the credit ratings literature uses data from only one CRA, normally Moody's or S&P. The literature which considers multiple CRAs predominantly focuses on Moody's and S&P only. Chapter 2 discusses these aspects. Further, the bulk of the rating market share is held by Moody's and S&P (over 80% according to SEC, 2018). On this basis, Fitch ratings do not enter any of the sample selections.

[2] Livingston et al. (2010) argue that split ratings signal information opaqueness and information asymmetry problems faced by CRAs in the rating process.

split rated peers and this potentially has a significant impact on investors' and issuers' behaviour.

The thesis answers three main research questions. Firstly, what is the impact of split ratings on the cost of equity capital? Secondly, what is the impact of split ratings on firms' debt maturity decisions? Finally, what is the impact of split ratings on firms' capital structure decisions? These three questions are addressed in Chapters 3 to 5, respectively. Additionally, Chapters 3 to 5 explore questions of whether split ratings comprising superior Moody's ratings relate to different outcomes compared to split ratings with superior S&P ratings. All empirical chapters in the thesis use the comprehensive credit rating (CCR) numerical scale to estimate the split ratings between two CRAs, Moody's and S&P. The CCR scale not only takes into account issuers' actual rating levels, but it also considers issuers' credit outlook and watch statuses. Thus, the advantage of using the CCR scale is that it conveys all available information that CRAs provide to the market. This approach to corporate split ratings is new to the literature.

In order to answer these research questions, the thesis employs various methodologies. Chapter 3 employs a cross-sectional model to generate forecasted earnings and then estimates the cost of equity capital. Chapters 4 and 5 examine the research questions using ordinary least squares (OLS) estimation initially. However, because both debt maturity and capital structure are limited dependent variables, the Tobit model and the Generalized Linear Model (GLM) are implemented to address the limitation of OLS in cases of proportional dependent variables. Additionally, all three empirical chapters apply the propensity score matching (PSM) method to address a potential endogeneity issue within the main regression models. Various matching methods are employed, namely, nearest neighbour matching with and without replacement, caliper matching, radius matching, kernel matching and Mahalanobis matching.

Chapter 3 examines the impact of split ratings on the equity market, using a panel dataset of all U.S. corporations rated by both Moody's and S&P from 2003 to 2017. One obstacle for Chapter 3 is to estimate the cost of equity capital because it is not as readily available as the cost of debt. In order to overcome this issue, Chapter 3 employs the cross-sectional model suggested by Li and Mohanram (2014) to generate the forecasted earnings because the model has been demonstrated to outperform the analyst-based model (Hou et al., 2012; Li and Mohanram, 2014). The results from the empirical investigation show that split ratings have a significant impact on the cost of equity capital. The disagreement between the two CRAs, Moody's and S&P, could signal uncertainty about firms' creditworthiness as well as information opaqueness/asymmetry problems surrounding firms. Equity investors recognize the greater information asymmetry problem signalled by split ratings and charge a higher premium for the extra uncertainty. This is consistent with Livingston et al.'s (2010) finding that split ratings bring new information to the market. In addition, split rated firms with superior Moody's ratings have a higher cost of equity capital compared to those with superior S&P ratings. This suggests that equity investors differentiate between Moody's and S&P when they disagree with each other. Thus, this evidence indicates that equity investors place more weight on S&P than Moody's, a more conservative CRA, when assessing firms' cost of equity capital. This contrasts with Livingston et al.'s (2010) finding that bond investors assign more weight to the conservative CRA, Moody's. Nevertheless, this difference could plausibly be due to the contrasting perspectives of bond investors (issuers' debtors) and equity investors (issuers' owners).

Chapter 4 tests two competing viewpoints regarding the impact of split ratings on firms' debt maturity decisions (see Section 4.3) using a panel dataset of all U.S. corporations rated by Moody's and S&P from 2003 to 2015. The first viewpoint is that firms with split ratings should issue more short-term debt. The signalling theory suggests that firms with greater information asymmetry problems should use more short-term debt to signal their financial strength and to reduce the information asymmetry. In addition, previous literature finds evidence that split ratings increase long-term borrowing costs (Livingston et al., 2010). Thus, under this viewpoint, split rated firms have more incentive to issue short-term debt in order to avoid the higher borrowing cost arising from split ratings. The opposite viewpoint is that split ratings encourage firms to use more long-term debt. Under this viewpoint, in order to avoid being assigned unfavourable future rating changes and rollover risk, split rated firms may prefer to issue at the long end of the maturity spectrum.[3] The empirical results of Chapter 4 confirm the latter viewpoint that split rated firms rely more on long-term debt than their non-split rated peers. This suggests that firms with split ratings are more concerned with future rating deterioration and the rollover risk associated with those changes than the current potential higher borrowing cost arising from split ratings. This is consistent with Gopalan et al.'s (2014) findings that firms with greater exposure to rollover risk are more likely to be downgraded severely by CRAs. In addition, the results of Chapter 4 also reveal that firms' managers differentiate between split ratings with superior Moody's ratings and those with superior S&P ratings. This suggests that

[3] Gopalan et al. (2014) suggest that firms with higher exposure to rollover risk (use more short-term debt) are more likely to receive rating downgrades and to have higher long-term borrowing cost.

firms' managers put different weights on Moody's and S&P ratings when deciding upon an optimal debt maturity structure.

Chapter 5 examines the impact of split ratings on firms' capital structure decisions under three different capital structure theories, namely the trade-off theory, the pecking order theory and the market timing theory (see Section 5.3). The trade-off theory states that firms' decisions regarding optimal capital structure are based on the trade-off between the marginal benefit of tax-shields and the marginal cost of bankruptcy (Kraus and Litzenberger, 1973). Under this theory, because of the higher long-term borrowing cost arising from split ratings, split rated firms will be motivated to move towards the zero-debt policy and issue less debt. Secondly, the pecking order theory argues that firms' choice of financing sources (retained earnings, debt and equity) depends on the level of adverse selection arising with these sources (Myers, 1984). Retained earnings have no adverse selection problem, debt has a minor problem, while equity has a serious problem (Frank and Goyal, 2009). Thus, according to pecking order theory, split rated firms, who already have a greater information asymmetry problem than their non-split rated peers, would rely more on debt issuance than equity.[4] Lastly, the market timing theory states that firms' capital structure decisions are based on which of the two markets, debt or equity, are more favourable at the time (Frank and Goyal, 2009). Under this theory, split rated firms will choose the source of financing that is less affected by the split ratings.

Similar to Chapter 4, Chapter 5 uses a dataset of all U.S. corporations rated by the two major CRAs from 2003 to 2015. The empirical results from Chapter 5 reveal that split ratings have a significant impact on firms' optimal capital structure. Split rated firms, on average, have a higher level of their optimal level of leverage compared to non-split rated firms, suggesting that firms with split ratings are more concerned about the information asymmetry problem signalled by CRAs' disagreement than the potential increase in borrowing cost arising from split ratings. This is consistent with evidence from the equity market where firms with greater information asymmetry rely more on debt than equity (Petacchi, 2015). In addition, there is evidence that firms do not differentiate between Moody's and S&P ratings regarding capital structure decisions when split ratings occur. This contrasts with evidence from the corporate bond market where investors put more weight on Moody's ratings than S&P ratings when assessing firms' creditworthiness. This also contrasts with the findings of Chapter 3 and 4, which suggest that equity investors and firms' managers (when assessing the debt maturity

[4] Previous literature shows that firms with substantial information asymmetry problems rely more on debt financing than firms with low level information asymmetry problems (Bharath et al., 2009; Petacchi, 2015).

structure) differentiate between split ratings comprising superior Moody's ratings and those with superior S&P ratings.

In general, CRAs' disagreement about U.S. firms' creditworthiness contributes additional information to the market. Much is still unknown about the impact of split ratings on the behaviour of firms and investors. Thus, this thesis makes a substantial contribution to the understanding of corporate split ratings and how they impact upon firms' and investors' decisions. The thesis contributes to the literature on credit ratings in four aspects. First, the thesis furthers the understanding of the significant impact of split ratings on the equity market, which arises from split ratings representing additional information to the equity market. Chapter 3 demonstrates that equity investors recognise the ambiguity arising from CRAs' disagreement about firms' creditworthiness and require a premium from split rated firms for this extra uncertainty. In addition, equity investors place more weight on S&P ratings than Moody's when they disagree with each other about firms' credit risk. This suggests that both ratings from Moody's and S&P bring information to the equity market and that equity investors are sophisticated in their recognition of this information. The thesis adds to previous literature (e.g., Bhattacharya et al., 2012, Fu et al., 2012) on the direct link between information asymmetry and the implied cost of equity capital. The thesis uses split ratings as a proxy of information asymmetry, which is directly and unequivocally observable, which is unlike some other measures of information asymmetry used in prior literature. In addition, the thesis complements the existing credit rating literature on the information production of split ratings and credit ratings (e.g. Livingston et al., 2010) by extending the perspective of split ratings to the equity market.

Second, the thesis provides an insight into how firms' decisions regarding debt maturity and capital structure are affected when split ratings occur. Chapter 4 provides insights into how split ratings affect firms' decisions on the optimal debt maturity structure. The results show that firms' managers take into account the information arising from CRAs' different opinions about their creditworthiness and adjust their optimal debt maturity accordingly. The results reveal new evidence on a previously unexplored link between split ratings and firms' behaviour regarding debt maturity structure. The findings reveal that firms are more concerned with the potential increase in roll-over risk in the future than the immediate increased cost of debt which coincides with split ratings. Chapter 5 demonstrates that CRAs' disagreements on corporate ratings also have a significant impact on firms' capital structure decisions and that firms are more concerned with information asymmetry (adverse selection) problems arising from split ratings than with any immediate increase in borrowing cost. Thus, Chapters 4 and 5 show that firms' optimal debt maturity and capital structure are affected by both CRAs' opinions, suggesting that ratings from both Moody's and S&P are indeed important to firms' managers. The thesis uses an accounting-based measurement of debt maturity structure, which supports previous literature. For example, Berger et al. (2005) measure debt maturity using bank loans. The thesis also provides empirical evidence for the information asymmetry models of Flannery (1986) and Diamond (1991). Consistent with Livingston et al. (2010), the thesis also finds evidence supporting the hypothesis that split ratings are a signal of information asymmetry (information opacity). While previous literature (Petacchi, 2015) finds that information asymmetry between investors has a significant impact on firms' capital structure, this thesis shows that the information asymmetry between firms and outsiders has a significant effect on firms' behaviour regarding capital structure and debt maturity. Thus, the thesis contributes to the understanding of capital structure decisions with regard to information asymmetry, split ratings and credit ratings. Additionally, the thesis employs the propensity score matching (PSM) to address any potential endogeneity concerns. By using this methodology, the thesis is able to evaluate and separate the information asymmetry arising from split ratings apart from the information asymmetry arising from other sources.

Thirdly, the thesis further confirms that there are indeed systematic differences between CRAs' evaluations of credit ratings and that these differences do not arise from random errors because firms' managers and investors recognise these disagreements and act accordingly. This implies that ratings from the two CRAs should not be treated as being entirely the same as each other. Finally, the thesis provides insights on how investors and firms' managers react differently in response to superior ratings being assigned by one CRA compared to superior ratings being assigned by the other. The thesis shows that investors and firms' managers react differently when facing split ratings comprising superior Moody's ratings versus those with superior S&P ratings. This suggests that investors and firms' managers have distinct CRA-based preferences and they place more emphasis on different CRAs dependent on the context of their decision making.

Table 1.1 highlights the contributions of the thesis in comparison with the key relevant literature.

The thesis is organized as follows. Chapter 2 reviews the literature on credit ratings, multiple ratings and split ratings. Chapter 3 examines the impact of split ratings on the cost of equity capital. Chapter 4 investigates the impact of split ratings on firms' debt maturity decisions. Chapter 5 investigates the impact of split ratings on firms' capital structure decisions. Chapter 6 concludes the work, including a discussion of the thesis' limitations and potential future research directions.

Table 1.1. The contributions of the thesis in comparison with key relevant literature.

A. Split ratings and the cost of equity capital			
Studies	Sample/ Measurements of Information asymmetry	Findings	Contributions of the thesis
Bhattacharya et al. (2012)	U.S. firms, 1993 to 2005. Earnings quality, the bid-ask spread and PIN (the probability of informed trading) as proxies of information asymmetry.	They find evidence of a direct link and indirect link (via information asymmetry) between the information risk (earnings quality) and the cost of equity capital. The direct link suggests that it is advantageous for firms to increase the quality of information released.	- A more recent sample of U.S. firms from 2003 to 2017. - In contrast to related information asymmetry literature (Bhattacharya, 2012; Fu et al., 2012), split ratings are used in the thesis as a proxy of information asymmetry because split ratings are directly and unequivocally observable. - The thesis provides evidence on the significant impact of split ratings on the cost of equity capital. - The thesis confirms the direct link between information asymmetry and the cost of equity capital. Equity investors price the information risk when assessing firms' cost of capital, consistent with the findings of Bhattacharya et al. (2012) and Fu et al. (2012). - The thesis contributes to the literature on information production via split ratings (Livingston et al., 2010; Livingston and Zhou, 2010) and extends the perspective to the equity market. - The thesis shows that both CRAs contribute valuable information to investors and that investors differentiate between these CRAs when assessing the cost of equity capital. - In contrast to Livingston et al.'s (2010) findings, equity investors place more emphasis on S&P ratings than Moody's ratings when assessing the cost of equity capital.
Fu et al. (2012)	U.S. firms, 1951 to 1973. The bid-ask spread and price impact as proxies for information asymmetry.	They find that higher financial reporting frequency reduces information asymmetry and the cost of equity capital, thereby suggesting that there is a link between information asymmetry and the cost of equity capital.	
Livingston et al. (2010)	Non-financial U.S. corporate bonds, 1983 to 2008. Split ratings as a signal of information opacity.	They find that bonds with split ratings on average have a higher yield than non-split rated bonds. Furthermore, they find that a split rated bond with superior Moody's ratings has lower yields than a split rated bond with superior S&P ratings.	
Livingston and Zhou (2010)	U.S. bond issues from 1983 to 2008. Split ratings as a proxy of information opacity	They find that split ratings are indeed a signal of information opacity and bond investors require a premium for the information opacity associated with split ratings.	

B. Split ratings and debt maturity			
Studies	Sample/ Measurements of Information asymmetry	Findings	Contributions of the thesis
Berger et al. (2005)	U.S. bank commercial loans in 1997. Employment of small business credit scoring (SBCS) technology as a proxy of information asymmetry.	The study finds that low-risks firms are more likely to have shorter debt maturities than other firms, suggesting that information asymmetry is indeed a determinant of debt maturity.	- Since Berger et al.'s (2005) empirical tests are based on bank loans, the thesis makes contributions to the literature by exploring the effect of information asymmetry on firms' debt maturity structure. - Consistent with the information asymmetry model of Flannery (1986) and Diamond (1991) as well as the empirical evidence of Goyal and Wang (2013), the thesis finds that firms with a greater information asymmetry problem (split ratings) prefer to issue more long-term debt. - The thesis contributes to the debt maturity and information asymmetry literature by providing evidence that split ratings, as a proxy of information asymmetry, have a significant impact on firms' optimal level of debt maturity. - The thesis shows that split-rated firms rely more on long-term debt (scaled by total debt), thereby suggesting that firms with greater information asymmetry tend to reduce their exposure to rollover risk. Thus, this result is consistent with Gopalan et al.'s (2014) findings. - Consistent with Livingston et al.'s (2008) findings, the thesis shows that split rated firms rely more on a longer debt maturity structure in order to avoid receiving future rating downgrades. - The thesis contributes to the literature on the impact of split ratings (Livingston et al., 2008; Livingston and Zhou, 2010; Livingston et al., 2010) by providing evidence that split ratings have a significant impact not only on investors' behaviour, but also on firm managers' behaviour regarding debt maturity decisions.
Goyal and Wang (2013)	U.S. debt issues, 1983 to 2003. Changes in future default risk as a proxy for information asymmetry.	They find a link between firms' information asymmetry and their debt maturity choice. Firms with unfavourable private information are more likely to issue long-term debt while firms with favourable private information prefer short-term debt.	
Gopalan et al. (2014)	U.S. long-term corporate bonds, 1986 to 2010.	They find that firms with greater exposure to a long-term debt payable within the year are more likely to be downgraded by CRAs.	
Livingston et al. (2008)	U.S. bond issues, 1983 to 2000.	They find that split rated bonds are more likely to receive rating changes within one year of initial issuance.	
Livingston et al. (2010)	Non-financial U.S. corporate bonds, 1983 to 2008. Split ratings as a signal of information opacity.	They find that the information asymmetry signalled by split ratings is priced by bond investors.	

<table>
<tr><td colspan="4">C. Split ratings and capital structure</td></tr>
<tr><td>Studies</td><td>Sample/ Measurements of Information asymmetry</td><td>Findings</td><td>Contributions of the thesis</td></tr>
<tr><td>Bharath et al. (2009)</td><td>U.S. firms, 1973 to 2002.
Information asymmetry index based on seven proxies of adverse selection.</td><td>Bharath et al. (2009) find that information asymmetry is an important determinant (but not a sole determinant) of firms’ leverage, supporting the pecking order theory (Myers, 2001).</td><td rowspan="3">- Compared to Bharath et al. (2009), the thesis uses a more recent sample of U.S. firms from 2003 to 2015.
- In contrast with Bharath et al. (2009), split ratings are primarily related to default risk and debt. Thus, using split ratings as a proxy of information asymmetry could identify the impact of changes in debt market information risk on the changes in firms’ capital structure.
- The thesis complements the existing capital structure theories by providing evidence supporting the pecking order theory, whereas firms with split ratings (a greater information asymmetry problem) rely more on debt issuance than do non-split rated firms (a lesser information asymmetry problem). Thus, the thesis contributes to the capital structure literature and extends the perspective to the effects of CRAs’ disagreement on firms’ behaviour.
- Petacchi (2015) focuses on the information asymmetry between equity investors and debt investors as the FD regulations only affect the equity market. Thus, by using split ratings as a proxy for information asymmetry, the thesis explores the link between information asymmetry (between outside investors and firm insiders) as well as the information asymmetry on the debt market and firm capital structure.
- The thesis also contributes to the understanding of capital structure decisions (e.g, Kisgen, 2006; Bharath et al, 2009; Petacchi, 2015). The thesis shows that firms’ managers are not only concerned about ratings but are also concerned about the disagreement between CRAs about firms’ creditworthiness. The thesis also demonstrates that these concerns translate into real economic decision-making consequences.</td></tr>
<tr><td>Petacchi (2015)</td><td>U.S. firms, 1996 to 2004.
Regulation Fair Disclosure (FD) as an exogenous shock.
Adjusted probability of information-based trading (AdjPIN) and bid-ask spreads as proxies for information asymmetry.</td><td>Petacchi (2015) finds that the information asymmetry in the equity market is positively associated with the firms’ greater reliance on debt.</td></tr>
<tr><td>Kisgen (2006)</td><td>U.S. corporations (excluding financial firms and utilities), 1986 to 2001</td><td>Kisgen (2006) finds that credit ratings directly affect firm managers’ capital structure decisions.
He finds that firms use less debt when they are near a rating change (firms with a plus or minus rating (e.g., BBB+ or BBB–)).</td></tr>
</table>

Chapter 2: Literature review

2.1 Introduction

Since the U.S. sub-prime mortgage crisis in 2007 – 2008 and the European sovereign debt crisis in 2010 – 2013, the credit rating industry has received a lot of attention. Credit rating agencies (CRAs) are considered to have played a significant role in both of these crises. The purpose of this Chapter is to provide an introduction to the CRAs and to explain the uses of credit ratings, along with a thorough review of the existing literature on CRAs which is most closely related to the theme of this thesis. More specific and focused literature reviews are included in Chapters 3, 4 and 5.

A credit rating is an assessment of a borrower's creditworthiness or the likelihood that the borrower will fulfil its obligation to the lenders or investors. That credit evaluation is generally carried out by independent CRAs, such as S&P and Moody's. Credit ratings are given in the form of a letter scale ranging from AAA/Aaa, the top credit quality to C/SD/D (see Table 2.1). The credit rating industry can be divided into many segments, namely corporate ratings, insurance ratings, sovereign ratings, structured-finance ratings and so on. In the U.S., the total revenue for 10 CRAs that certified as National Recognized Statistical Rating Organizations (NRSROs) in their 2017 fiscal year was about 7.1 billion dollars, about 1.2 billion dollars higher than the 2016 fiscal year figure (SEC, 2018). This shows that despite being subject to a considerable controversy during and after the global financial crisis, the credit rating industry has retained its size and reach.

CRAs play a central role in many financial markets as information intermediaries who alleviate the asymmetric information problems between investors and issuers. Issuers solicit ratings for a number of reasons, including to increase the marketability of their securities and/or to meet the requirement of regulators. Investors use credit ratings to manage their exposure to the credit risk of purchased securities. A large proportion of the debt markets is restricted by laws relating to the acceptable default risks to which investors can be exposed. For example, pension funds are only allowed to hold investment graded bonds (bonds which have ratings higher than BB+/Ba1, see Table 2.1). Moreover, not only are credit ratings used as indicators of borrowers' default risk, but they affect the interest rate at which the debt instrument will be charged. The lower credit rating normally means higher risks of defaulting, higher interest rate, and greater difficulty for firms or governments to access capital. Hence, maintaining a high and stable credit rating is important to issuers as it affects their borrowing costs and access to capital.

Apart from issuers and investors, there is regulatory use of credit ratings. In the U.S., the Securities and Exchange Commission (SEC) certifies certain CRAs as NRSROs and the ratings of those CRAs are permitted for further usage in various types of regulations. In Europe, the European Securities and Markets Authority (ESMA) is responsible for the registration and supervision of CRAs. If a CRA is registered or certified by ESMA, its ratings are permitted for regulatory purposes in the EU. For example, in the Basel III framework, credit ratings from registered CRAs can be used to decide the supervisory haircuts applying to financial collateral (see Basel Committee on Bank Supervision, 2015).

In the context of the credit rating industry, there are over 200 CRAs all over the world (Marandola, 2016) and the global bond market has reached an estimation of about 100 trillion dollars by 2018 (The Bank for International Settlements, 2018). In the U.S, as aforementioned, there are 10 NRSROs. However, the U.S credit rating industry is extremely concentrated as the two majors CRAs, whereby Moody's and S&P control 82.3% of the total market (SEC, 2018).[5] It is common that an issuer or a debt issue receives ratings from more than one CRA. Generally speaking, regulators and researchers normally treat CRAs equally. Hence, one might ask whether or not multiple ratings bring new information to the market, and whether more ratings mean better information. Furthermore, CRAs do not necessarily agree with each other on issuers' creditworthiness, and frequently assign different ratings to the same issuer at the same time. Split ratings occur when CRAs have different opinions about the creditworthiness of a given issuer at the same time. This is the predominant theme of this thesis. Therefore, this Chapter provides a detailed overview of the relevant literature regarding multiple ratings and split ratings.

The remainder of this chapter is organised as follows. Section 2.2 presents the fundamentals of multiple ratings, Section 2.3 outlines the causes and importance of split ratings, Section 2.4 explains issues relating to CRAs' business models. Finally, Section 2.5 presents the conclusions of this Chapter.

[5] In addition, Moody's and S&P ratings account for 59.8% of financial institutions, 43.7% of insurance companies, 71.2% of corporate issuers, 65.3% of asset-backed securities and 87.1% of government securities.

2.2 Multiple ratings

Multiple ratings occur when an issuer or debt instrument receives ratings from two or more CRAs, which could agree or disagree with each other. There are three hypotheses of the occurrence of multiple ratings, namely information production hypothesis, rating shopping hypothesis and regulatory certification hypothesis.

2.2.1 Information production hypothesis

From the beginning, the "natural" users of rating have been debt issuers. Although credit ratings do not determine issuers' ability to enter the financial market, they can have huge effects on issuers' operations, both in terms of capital accessibility and borrowing cost. Credit ratings are the indicator of borrowers' creditworthiness, which is their likelihood to pay back their debt obligations. Hence, higher ratings mean better credit quality, lower credit risk, and better improvement of both bond marketability and reputation. Issuers who obtain good ratings can raise capital through the market by insuring investors with preferences over ratings because ratings are also be used by institutional investors, financial intermediaries and regulators to assess securities' risk and the likelihood of repayment (Becker and Milbourn, 2011). Furthermore, some agreements, contracts or transactions might require firms to be at a particular rating (e.g., investment-grade rating).

Given the important role of credit ratings on mitigating information asymmetry problem between issuers and investors, issuers soliciting multiple ratings might be motivated by the improvement in information production. Because CRAs might rely on a different kind of information when evaluating the creditworthiness of issuers/issues, multiple perspectives could bring additional information to the market and therefore reduce the uncertainty about borrowers' creditworthiness. Baker and Mansi (2002) and Drago and Gallo (2018) find that the uncertainty on the credit quality could be reduced with additional ratings.[6] Baker and Mansi (2002) argue that multiple ratings increase the probability of accurate evaluation of creditworthiness and hence produce the best possible outcome in terms of borrowing cost (see, for example, Hsueh and Kidwell, 1988).[7] Therefore under the information production hypothesis, one might expect issuers with greater information asymmetry/information

[6] Morkoetter et al. (2017) also find evidence of information production hypothesis regarding the U.S. residential mortgage-backed securities.
[7] Drago and Gallo (2018) find that multi-rated firms have lower syndicated loan spreads. They find evidence of the three hypotheses with regards to syndicated loan spreads.

opaqueness problem to seek extra opinions because it would raise their chance of potentially reducing uncertainty (Bongaerts et al., 2012).

2.2.2 Rating shopping hypothesis

Under rating shopping hypothesis, issuers may shop around for favourable ratings because they can decide whether their ratings are publicly published or not. Since issuers have better information about their credit risk, when CRAs disagree with each other about their creditworthiness, issuers could maximize their ratings by using stop rules and choose the first firms that assign ratings better or equal to their own assessment of ratings (Bongaerts et al., 2012). Faure-Grimaud et al. (2009) show that issuers only hide their ratings if they are uncertain about their creditworthiness and if the decision of obtaining ratings is not observable. Bolton et al. (2012) argue that competition among CRAs can reduce market efficiency because of the rating inflation arising from rating shopping. Drago and Gallo (2018) find evidence of rating shopping in the bank syndicated loan market. They find that firms with less than three ratings (an indication of potentially shopping for better ratings) have greater loan spreads, suggesting banks price the risk of a potential rating shopping. They also find that banks' concern about rating shopping is greater during crises.

2.2.3 Regulatory certification hypothesis

Credit ratings directly tie to numerous regulation and legal rules. Demirtas and Cornaggia (2013) observe "virtually all financial regulators—including public authorities that oversee banks, thrifts, insurance companies, securities firms, capital markets, mutual funds, and private pensions—rely on the NRSRO concept in setting capital requirements". Because bond ratings or issuer ratings can be classified into two categories: investment graded and speculative graded, a number of regulations restrict market participants to hold a specific grade of bonds. For example, banks and insurance companies are required to have higher reserves for holding speculative-grade corporate bond than investment-grade ones. Other institutions like pension funds or mutual funds are subject to a restricted amount of speculative-grade bonds or securities that they can hold. Campbell and Taksler (2003) find that half of corporate bonds held by institutions are subjected to the rating-based restriction. Thus, getting into the investment-grade could grant issuers better access to the capital market.

Given the heavy reliance on the regulatory certification of credit ratings, multiple ratings are important to firms because additional ratings could help firms to reach regulatory requirements, especially the investment-grade rating classification. Bongaerts et al. (2012) find that firms are more likely to seek additional ratings (Fitch's rating) when ratings from Moody's and S&P are on the opposite side of the regulation boundary (investment grade boundary). Hence, Fitch in these cases plays the role of a "tiebreaker" and will decide which categories that the firms will fall in. Therefore, under the regulatory certification hypothesis, firms will seek ratings from a systematically more generous CRAs to satisfy regulatory requirements.

2.2.4 Multiple ratings and investors

Even though issuers are the instigators of solicited ratings from CRAs, credit ratings are also widely used by investors. Gonzalez et al. (2004) state that "Regulators (in regulations), banks and bondholders (in loan and bond covenants), pension fund trustees and other fiduciary agents (in investment guidelines, insurance company charters, etc.) have made increasing use of ratings-based constraints in their rules". Hence, the influence of CRAs upon the market has become more and more significant to the extent that their ratings appear in every aspect of financial markets. There are two reasons behind the usage of ratings: to reduce the adverse selection problem and to reduce the principal-agent problem (Gonzalez et al., 2004).

The first economic rationale for the use of ratings is the reduction in adverse selection/information asymmetry problem between investors and issuers. CRAs have an information advantage (economies of scale) because they are better at gathering information about issuers and evaluating of issuers' creditworthiness than individual investors or individual analysts. Hence, by giving their assessment of issuers' credit risk in the form of ratings, CRAs could improve the accessibility of borrowers to debt market as well as reduce the adverse selection problems caused by the information asymmetries between issuers and investors.

The second economic reason for the use of ratings is to eliminate the principal-agent problems. The principal-agent problems happen when agents are less likely to be motivated when their actions are hard to monitor or control directly. In this circumstance, by using ratings as the role of rules or guidance, issuers are able to monitor and control the actions of issuers and hence, reduce the possibility of principal-agent problems. This rationale is further confirmed by Cantor et al. (2007), in which they argue that the use of ratings as a governance tool to tackle the principal-agent problems is widespread among market participants.

Despite the increased reliance of investors, credit ratings are more likely to be used as inputs rather than the sole criterion by sophisticated investors in their investment procedure. Baker and Mansi (2002) argue that investors only need opinions from one or, at most, two of the largest CRAs. Thus, this contrasts with issuers as they need more ratings to reduce the information uncertainty of their bond.

Overall, investors use credit ratings in their investment decisions for two reasons: to reduce adverse selection and principal-agent problems.

2.3 Split ratings

Even though multiple ratings are common, CRAs frequently assign different ratings at the same time to issuers. Thus, split ratings occur when two or more CRAs disagree about issues' or issuers' creditworthiness. However, how this disagreement is defined is important in conducting studies on split ratings.

2.3.1 Definition of split ratings

In previous literature context, there are two ways that a split rating could be defined. The first one is to define split ratings based on the conventional numerical scale, which considers split ratings as the difference between CRAs' credit ratings at notch-level (i.e. A+ and A, or BB– and B+). Based on this definition, CRAs' rating scales are normally transformed into a numerical scale ranging from 1 to 18, 20 or 22 (Livingston et al., 2008, 2010; Alsakka and ap Gwilym, 2009, 2010) (see Table 2.2). This approach is simple and easy to apply because the largest CRAs have similar rating scales (as can be seen in Table 2.2). However, one drawback of this approach is that it does not account for outlooks/watches assigned by CRAs. Outlooks (watches) indicates potential rating changes over one or two years (three to six months). Previous studies show that outlook and watch signals contain important information about issuers'/issue's credit risk (see, for example, Hill et al., 2010; Chan et al., 2011; Hill et al., 2018; Hill et al., 2019).

The second approach is to define split ratings based on the comprehensive credit rating (CCR) numerical rating scale. In this approach, the letter ratings are also mapped into a numerical scale as a linear transformation (AAA/Aaa = 58, AA+/Aa1 = 55…CCC-/Caa3 = 4, CC/Ca to C/SD/D = 1). Additionally, outlooks and watches are transformed into value (e.g. -1 for negative outlook, +1 for positive outlook (Ferreira and Gama, 2007) and -2 for negative credit watch, +2 for positive credit watch (Sy, 2004; Vu et al., 2015)) and then added to the numerical ratings (See Table 2.2 for more details). Introduced by Sy (2004), the 58-unit CCR numerical score is used in a number of studies (Alsakka and ap Gwilym, 2012c; Vu et al., 2015; Vu et al., 2017). An issuer might receive the same ratings from CRAs but with different outlooks/watches, and the CCR numerical scale can capture such disagreements about firms' creditworthiness between two CRAs.

Another potential issue regarding the definition of split ratings is the time frame of the split. Existing literature only defines split ratings when there is disagreement among the CRAs at the initial bond issuance (Ederington, 1986; Livingston and Zhou, 2010). This method is sufficient with bond issues since they got rated at the time of issuance. However, with issuer ratings, it becomes more complicated because issuer ratings change over time. For example, when a CRA change the rating of an issuer to be different from other CRAs' ratings and hence, split rating occurs; however, in just short period of time, the other CRAs change their ratings accordingly and the split gets eliminated. In these circumstances, the split is short-lived and one might argue that if it only occurs in just short period of time, the split would be just the lag between CRAs' announcements or it could be just due to the timing differences in rating process/rating procedure. Hence, in order to truly include the split without counting "false" split ratings, a time frame restriction should be included in the rating scales. In this thesis, split ratings are calculated using an annual time frame and are rounded to remove short-lived split ratings (more details are discussed in Section 3.4.4).

2.3.2 Causes of split ratings

Several studies examine the reasons for the occurrence of split ratings. In this subsection, various causes of split ratings between corporate issuers/issues are examined (See Table 2.3 for a summary of studies on the causes of split ratings).

The starting point is the random error hypothesis. Random error hypothesis suggests that the cause of rating disagreement between CRAs is simply the random error. The error could be due to the sophistication of the evaluation procedure, and/or the difficulty of assessing credit risks (Ederington, 1986), or lack of experience for sovereign counterpart (Cantor and Packer, 1996). Hence, under this hypothesis, there are no systematic differences between the CRAs. CRAs are considered to have a similar methodology and use the same group of important determinants. This hypothesis is introduced by Ederington (1986) and further confirmed by Jewell and Livingston (1998) and Cantor and Packer (1996). Jewell and Livingston (1998) argue that because of the random error, investors will not differ between the two CRAs and consequently, the yield on split rated bond should be an average of the two ratings. However, the dataset that both Ederington (1986) and Jewell & Livingston (1998) used is the U.S. industrial bonds.

The second possible reason for the occurrence of split ratings is that there are systematic differences in the rating methodologies employed by CRAs. In contrast with the random error hypothesis, which suggests that split ratings are the product of unsystematic errors, the systematic difference hypothesis argues that split ratings are the result of CRAs using different rating methodologies and different evaluation processes. The systematic difference hypothesis implies that CRAs use different sets of core determinants, apply different weights to those determinants, and pursue distinctive credit assessment methodologies in the evaluating procedure (Moon and Stotsky, 1993; Pottier and Sommer, 1999; Livingston et al., 2008, Livingston et al., 2010; Alsakka and ap Gwilym, 2012a; Chen and Hill, 2013). Moon and Stotsky (1993) show that the set of rating determinants used by CRAs are not identical in the municipal bond industry. Pottier and Sommer (1999) find similar results in the insurer rating industry and they further explain that split ratings are also the result of different rating models employed by CRAs.

Furthermore, among the existing literature on different rating methodologies employed by CRAs, the heterogeneity of rating scales is also suggested as a possible cause of split ratings (Cantor and Packer, 1994; 1997; Livingston et al., 2008). This argument suggests that split ratings occur simply because CRAs use different rating scales. CRAs might agree with each other on the fundamental creditworthiness of an issuer; however, because of the heterogeneity of mapping to the rating scales, they assign different ratings to that issuer. Thus, split ratings occur even when CRAs do not disagree with each other over issuers' credit risk. This hypothesis indicates that there is indeed a systematic difference in the rating process between CRAs rather than random error. Cantor and Packer (1994, 1997) and Livingston et al. (2008) confirm that differences in rating scales across CRAs are one reason behind split ratings. However, Dandapani and Lawrence (2007) argue that the heterogeneity of rating scales is not the sole explanation of CRAs' apparent disagreement about ratings, but without explicitly specifying the other reasons. Despite these views in one strand of the literature, almost all credit rating literature uses the same numerical scales (either the conventional scales or the comprehensive numerical scales). It is therefore appropriate that this thesis does not consider the heterogeneity of rating scales to be the central issue associated with observing split ratings.

In addition, split rating could be the result of different precise definitions of issuer ratings by Moody's and S&P. While S&P issuer ratings are designed to reflect the probability of default (PD) of an issuer, Moody's issuer ratings represent both PD and loss given default (LGD) (Chen and Hill, 2013). More broadly, there is a greater tendency by Moody's to focus on specific issue-level considerations and hence they have a proliferation of different rating types which also evolves over time. Hence, it is possible that split ratings are the result of this aspect of the methodologies applied by the two CRAs. However, both researchers and practitioners demand comparability in order for ratings to be analysed, and the CRAs have responded according to the underlying premise that ratings will be less widely used if a lack of comparability is perceived. Consequently, when comparing S&P and Moody's ratings, the vast majority of the credit rating literature assumes that an issuer-level credit rating is an assessment of overall creditworthiness, and essentially considers default (PD) rather than LGD (e.g., Bharath and Shumway, 2008; Livingston et al., 2010; Livingston and Zhou, 2010 and a vast set of more recent literature).

The information opacity hypothesis suggests that it can be difficult for CRAs to assess issuers' fundamentals because of the asset opacity and that this is a potential cause of split ratings (Morgan, 2002; Livingston et al., 2007; Livingston et al., 2010; Livingston and Zhou, 2010). Morgan (2002) finds that banks and insurance firms are more likely to receive split ratings from CRAs. Morgan (2002) argues that this phenomenon happens because firms in both the banking and insurance industries present CRAs with greater difficulties arising from asset opacity. Consistent with Morgan (2002), Iannotta (2007) also finds that bank opacity problem is the cause of disagreement between CRAs. The link between asset opacity and split ratings is also confirmed by Livingston et al. (2007) for the non-bank firms. The hypothesis implies that firms with a higher extent of asset opacity are more likely to receive split bond ratings from the CRAs. Livingston and Zhou (2010) argue that while split ratings could be the outcome of random errors or of information opacity, investors cannot easily distinguish between split ratings caused by random error and split ratings caused by information opacity. Consequently, risk-averse investors will assume the existence of split ratings as a sign of information opacity and thus, a yield premium for these issuers' debt securities is required. They further argue that multiple-notch split ratings are less likely to be caused by random error and that investors will require an even higher premium for holding such debt securities. Livingston and Zhou (2010) find evidence supporting the information opacity hypothesis. They find that bond investors require a higher premium for split rated bonds than non-split rated bonds with similar credit risk, implying that the random error is less likely to be the cause of split corporate ratings. In addition, they further strengthen the information opacity hypothesis by providing evidence that investors demand higher premia on debt with multiple-notch split ratings than with one-notch splits.[8,9]

In addition, one potential cause of split ratings could be the influence of large shareholders of CRAs. Using a dataset of 9,550 U.S. new bond issued from 2001 to 2010, Kedia et al. (2017) find that Moody's assign about 0.467-notch higher ratings than S&P for bonds that issued by firms in which the two major Moody's shareholders (Berkshire Hathaway and Davis Selected Advisors) are investing. They further argue that the way that the large shareholders could exert influence on Moody's analyst is through the threat of exit and voice. The threat of intervening or selling their shares could be sufficient enough to alter Moody's managers' behaviour. Thus, this suggests that Moody's is less objective in comparison with other CRAs when rating firms/issues of firms in which its large shareholders are investing. Consequently, this leads to different opinions about firms'/issues' creditworthiness between Moody's and the other CRAs.

2.3.3 Split ratings between Moody's and S&P ratings

The thesis focuses on issuers' (corporations') split ratings between Moody's and S&P. Thus, one specific cause of split ratings, in this case, is the different rating methodologies that Moody's and S&P use to evaluate issuers' default risk (ratings by both CRAs are assigned to both debt issues and issuers).

While S&P ratings are assigned to an issuer to reflect the probability of that issuer default on its debt, Moody's ratings are designed to reflect both the probability of default (PD) and the loss given default (LGD) (Chen and Hill, 2013). Thus, two identical bonds with different security will be assigned different ratings by Moody's (as their LGD are different) but not by S&P (as their PD are the same). Güttler and Wahrenburg (2007) argue that for speculative firms, the two CRAs could assign different ratings even though they share an identical view on the PD because LGD considerations are more applicable for these firms.

[8] Rating solicitation is another potential explanation for split ratings. Solicited ratings are assigned by CRAs at the request of the issuers, while unsolicited ratings are assigned by CRAs but without the issuers' involvement. Poon (2003), Poon and Firth (2005), Van Roy (2005) and Poon et al. (2009) find that unsolicited ratings are likely to be lower than the solicited ratings.

[9] Another explanation for the cause of split rating in both non-sovereign and sovereign ratings is the home region bias effect. Under this hypothesis, an issuer could receive a higher rating from the CRAs operating in the same areas as the issuer. The rationale behind this hypothesis is that CRAs, particularly the smaller ones, have a better understanding and more experience in their home regions and hence, their evaluation is somewhat different from the other CRAs operating in different regions. Shin and Moore (2003), Alsakka and ap Gwilym (2012b) and Yalta and Yalta (2018) find evidence that CRAs bias to specific regions or country.

In addition, the thesis uses issuer ratings from both CRAs to measure the split ratings; however, the method of assigning these ratings differs from Moody's and S&P. While S&P provides specific issuer ratings, Moody's assign the senior unsecured rating as issuer ratings. This could potentially lead to differences between Moody's and S&P ratings as S&P ratings are more likely to align with issuer ratings (Kisgen, 2006). In addition, as Moody's issuer ratings are not available for all of the issuers, the corporate family ratings and senior unsecured ratings are used instead in this thesis and by many other researchers.

However, existing literature and market participants do not consider Moody's and S&P issuer ratings to have material conceptual differences. Many examples from prior literature (e.g., Mahlmann, 2009; Livingston et al., 2010; Bongaerts et al., 2012) use Moody's ratings while assuming that they represent an assessment of the probability of default rather than loss given default, and thus, Moody's and S&P ratings are inherently comparable. Therefore, much previous literature on credit ratings typically considers Moody's and S&P rating to be interchangeable. For example, even though Rauh and Sufi (2010) use Moody's issuer ratings in their samples, they still consider that Moody's and S&P ratings are comparable and interchangeable as they suggest that S&P ratings could be used instead of Moody's ratings. Given these reasons, the differences in rating methodology of Moody's and S&P with regard to issuer ratings do not impose a large bias upon the investigations in this thesis.

2.3.4 The impact of split ratings

Research on the information content of split ratings has been predominantly focused on the corporate segment of credit ratings. The impact of split ratings in the literature concentrates on which rating is incorporated in the price of bond in case of the split, the higher, the lower or the middle of two ratings. However, the results of previous studies on this matter are mixed. Some studies find that the inferior ratings are priced into the spread, while others argue that spread is determined by the superior ratings. In most of the studies, Moody's and S&P are the two CRAs to be compared as they are the dominant players of the rating market.

2.3.4.1 Split ratings and bond yields

Billingsley et al. (1985), Liu and Moore (1987) and Perry et al. (1988) suggest that the bond interest rate is driven by the lower rating of the two ratings. Hence, investors are biased toward the conservative CRAs. Livingston et al. (2010) also find evidence that bond investors put more weight (but not entirely) to Moody's, a more conservative CRA in U.S. corporate ratings, when assessing bond yields. On the other hand, Hsueh and Kidwell (1988) find that bond yield is more likely to be priced with the higher rating from the two CRAs. In this case, the borrowing cost for split rated bonds should be cheaper for the issuers compared to their non-split rated peers.

A number of studies find that split ratings bring new information to the market and thus, split ratings have an impact on the borrowing cost or bond spreads (Perry et al., 1988; Elton et al., 2004; Mahlmann, 2009; Livingston et al., 2010; Livingston and Zhou, 2010). Livingston and Zhou (2010) find that bond yield of one-notch split rated issues has on average 7 basis point higher spread than those of non-split rated bonds of similar credit risk. The gap further increases to 15 and 20 basis point for two-notch and three-notch splits, respectively. Livingston et al. (2010) also find that on average bonds with superior rating from Moody's have lower yields than bonds with superior rating from S&P. This suggests that bond spreads are neither priced with the higher nor lower ratings but somewhere in between the two ratings. This implies that split ratings indeed bring new and important information to the market and investors recognize this information and charge split rated bonds accordingly.

When there are no split ratings, issues with multiple ratings are more likely to have lower yield compared to that of issues with same rating categories assigned by a single CRA (Hsueh and Kidwell, 1988). This view implies that none of the ratings from CRAs in the case of split ratings has any effects on yields and the price of bonds is decided by the average of the two ratings (Cantor and Packer, 1997; Jewell and Livingston, 1998).

2.3.4.2 Split ratings and rating migrations

The link between split ratings and rating changes are examined in a number of studies. Understanding this concept is important because rating migrations have a significant impact on both bond yields and price (Livingston et al., 2008). Livingston et al. (2008) find that split rated bonds are more likely to receive rating actions from CRAs in the future, whereby a one-notch split increases the probability of rating migrations by 3% to 6%. Livingston et al. (2008) show that a split rated bond is more likely to have its ratings downgraded (upgraded) by CRAs that assign superior (inferior) ratings within three years. In addition, split rated bonds that do not converge maintain their relative ratings (that is, the CRAs which assign superior ratings to maintain superior ratings and vice versa). Thus, Livingston et al.'s (2008) findings are consistent with the systematic difference hypothesis, which suggests that split ratings are not caused by random errors.

In the context of sovereign split ratings, Alsakka and ap Gwilym (2010) also find consistent results as in the corporate rating literature. They find that the sovereign issuers with split ratings are more likely to receive rating changes. They further show that the rating differences between CRAs tend to converge over time, which means CRAs that assign inferior (superior) ratings are more likely to upgrade (downgrade) their ratings. The bigger the differences in ratings, the greater the probability of future rating changes.

2.4 CRAs' business model

After the outbreak of the U.S. sub-prime and European sovereign crises, CRAs' business model has received numerous criticisms from investors, regulators and financial analysts. The controversy is which business models are suitable for CRAs and for the best of the market: the investor-pay model or issuer-pay model.

Before the 1970s, CRAs applied the investor-pays model, in which investors subscribe to CRAs for the ratings. In 1970 Moody's was the first CRA to adopt the issuer-pays model, which means issuers are the one who pays CRAs to rate their bonds or issue. This action of Moody's had set the change for the rest of the industry. Nowadays, most of CRAs use the issuer-pays model with only a few exceptions such as Egan-Jones which use the investor-pay model.

White (2010) discusses numerous possible reasons for the shift from investor-pay to issuer-pay model. Firstly, at that time the introduction of high-speed photocopy machine posed a threat to the ratings in terms of the sales of rating manuals, as many investors could obtain rating manuals free from their friends. Secondly, the bond market was shocked by the bankruptcy of Penn-Central Railroad in 1970. Bond issuers wanted to assure the bond investors about their risk and thus, were willing to pay CRAs to rate their issues/bonds. However, this is less likely to be the reason because investors would be the one more willing to pay if that kind of shock happened. Thirdly, in order to get their bonds to the portfolio of financial institutions, bond issuers need to obtain ratings from one or more CRAs and hence, they are willing to pay the CRAs to do so. Fourthly, as an information industry, the rating industry has a feature that the information can be paid for by the investors, or issuers or both of them.

After the financial crisis in 2002, CRAs failed to foresee Enron and WorldCom bankruptcy and the mortgage sub-prime crisis in 2007-2008, and CRAs provided inaccurate ratings for numerous asset-backed securities (ABS). Many policymakers have questioned the validity of the issuer-pays model and suggested CRAs should switch back to their former business model, investor-pays model. The rationale behind the concern about the issuer-pays model is the conflict of interest between accommodating issuers who pay for the ratings and assign a high-quality rating for investors who generate no revenue for CRAs. Jiang et al. (2012) and Xia and Strobl (2012) find that S&P assign higher ratings to firms or bonds with greater potential conflicts of interest, which is more likely to generate higher revenue for CRAs. Kashyap and Kovrijnykh (2016) investigate the optimal compensation schemes for CRAs of whether planners, firms or investors order the ratings and find that rating errors are larger when issuers order ratings than when investors do. They further argue that the investor-pay model will result in more precise ratings than the issuer-pay model.

However, changing back to the investor-pay business model could be a challenge for the rating industry. Big investors (i.e. financial institutions) have their own credit risk assessment, thus they do not need to pay for the ratings, while smaller investors may not be able to pay enough fee to keep the whole system running. Hence, Paul Taylor, Fitch Rating chief executive, stated "The reality is that you would not have a rating industry if that was the case (investor-pay model)" (Financial Times, 2013). The reason behind this argument is not only the fee that keeps the whole system running, but it also concerns the private information that CRAs can access under the issuer-pay model. With the investor-pay model, CRAs have to rely on the public information only and the ratings then might not be necessary informative since it only reflects the existing public information. Moreover, when CRAs assign ratings that rely solely on public information, unsolicited ratings tend to be lower than the case that CRAs are solicited and can access private information (Bannier et al., 2010). This means that without the private information of issuers, CRAs might not be able to assign accurate and quality ratings.

2.5 Conclusions

Because CRAs play a very important role in financial markets, they have received ever-increasing attention from regulators, investors and researchers. New legislation and additional rules have been announced to regulate CRAs after the global financial crisis. In the U.S., the Dodd-Frank Act was passed in July 2010 to eliminate the regulatory over-reliance on credit ratings. The main relevant aspects of the Dodd-Frank Act are (i) to increase the liability of CRAs for issuing inaccurate ratings and (ii) to better enable the U.S. SEC to impose sanctions on CRAs and to charge them in cases of material misstatements and fraud (for more details on the U.S. regulatory reforms of rating industry, see Dimitrov et al. (2015)). However, regulators, investors and academic researchers still treat CRAs equally in cases of multiple ratings and split ratings. The purpose of this Chapter is to explore the current literature regarding multiple ratings, split ratings and the impact of split ratings on equity investors' and firms' behaviour regarding the cost of capital, debt maturity and capital structure, which are the key themes of this thesis.

Previous literature provides three hypotheses to explain why firms solicit for multiple CRAs, namely: information production, rating shopping and regulatory certification hypothesis (see Bongaerts et al., 2012). The information production hypothesis suggests that additional ratings could bring new information to the markets and that issuers solicit for multiple ratings to reduce the information asymmetry between issuers and investors. The rating shopping hypothesis suggests that firms solicit for multiple ratings in order to shop for the most favourable ratings. The regulatory certification hypothesis suggests that firms opt for additional ratings to meet the regulatory requirement (for example, investment-grade ratings).

Split ratings literature suggests many potential causes of CRAs' disagreement on issuers' creditworthiness. Corporate split ratings could be due to random error, systematic differences in CRAs' rating scales, systematic differences in CRAs' rating methodology, firms' information opaqueness, home-bias effect and CRAs' bias toward large shareholders. Although sharing several common causes of split ratings, sovereign split ratings are particularly linked to political risk and the level of government transparency. Most of the split ratings causes (except for random error) imply that there is a systematic difference among CRAs and that the concept of treating CRAs as equal as each other is problematic. Furthermore, previous literature finds that split ratings have a significant impact on issuers' bond yields (see, for example, Livingston and Zhou, 2010; Livingston et al., 2010). Split rated issuers or issues are more likely to have higher borrowing cost compared to their non-split rated peers. Nevertheless, there are various gaps in the existing literature and a number of them are identified as follows.

While split ratings in debt instruments are common, their influence on equity markets or stock markets has received little attention. There are many academic studies that investigate the causes of split ratings and the relationship between bond yields and split ratings (Morgan, 2002; Livingston et al., 2010). However, to the best of my knowledge, there is not any previous study that analyses how the firms' cost of equity capital reacts to the disagreement among CRAs. It is important to understand this issue because differences in credit ratings can bring additional information and have a significant economic effect on the expected return of the issuer's stock, which in turn has a significant impact on investors' decision. Chapter 3 furthers the understanding of the impact of corporate split ratings on the equity markets, especially on the cost of equity capital.

Another notable gap in the existing literature is the impact of split rating on issuers' choices of debt maturity. One might ask whether or not split rated corporates might take action to alter their debt maturity structure. Chapter 4 examines the impact of split corporate ratings on debt maturity, as previous literature has focused on the impact on firms' borrowing cost (bond yields).

Previous literature has shown that credit ratings (especially rating actions) have a significant impact on firms' capital structure decision (Kisgen, 2006; 2009). One might ask whether split-rated corporate issuers have a different behaviour regarding optimal capital structure compared to their non-split rated peers. Thus, Chapter 5 investigates the impact of CRAs' disagreement upon firms' creditworthiness on firms' capital structure.

To summarize, this thesis furthers the literature on the impact of split ratings on firms' behaviour with regards to capital structure, debt maturity structure and cost of equity capital.

Table 2.1. CRAs' rating scales

	Moody's		S&P		
	Long term	Short term	Long term	Short term	
Investment Grade	Aaa		AAA		Highest
	Aa1		AA+	A-1 +	
	Aa2	Prime 1	AA		
	Aa3		AA-		
	A1		A+		
	A2		A	A-1	
	A3		A-		
		Prime 2		A-2	
	Baa1		BBB+		
	Baa2	Prime 3	BBB	A-3	
	Baa3		BBB-		
Non-Investment Grade	Ba1		BB+		
	Ba2		BB	B	
	Ba3		BB-		
	B1		B+		
	B2		B		
	B3	Not prime	B-		
				C	
	Caa1		CCC+		
	Caa2		CCC		
	Caa3		CCC-		
	Ca		CC		
	C		R		
			SD/D	D	Lowest

Note: Table 2.1 presents the detailed rating categories (long-term and short-term) of the two major CRAs, Moody's and S&P. *Source:* CRAs' rating definitions and scales from their own websites.

Table 2.2. Conventional and 58-unit rating scale

Moody's	S&P	Conventional rating scale	58-unit rating scale
Aaa	AAA	20	58
Aa1	AA+	19	55
Aa2	AA	18	52
Aa3	AA–	17	49
A1	A+	16	46
A2	A	15	43
A3	A–	14	40
Baa1	BBB+	13	37
Baa2	BBB	12	34
Baa3	BBB–	11	31
Ba1	BB+	10	28
Ba2	BB	9	25
Ba3	BB–	8	22
B1	B+	7	19
B2	B	6	16
B3	B–	5	13
Caa1	CCC+	4	10
Caa2	CCC	3	7
Caa3	CCC–	2	4
Ca	CC	1	1
C	C		
N/A	SD		
Outlook/Review	Outlook/Credit Watch	Value	Value
Review possible upgrade	CW-positive	0	+2
Positive	Positive	0	+1
Stable	Stable	0	0
Negative	Negative	0	-1
Review possible downgrade	CW-negative	0	-2

Note: Table 2.2 shows the two numerical scales, the conventional rating scale and the 58-unit comprehensive rating scale.

Table 2.3. Summary of the causes of split corporate and sovereign ratings

Common cause	Study	Type of data	CRAs	Sample size	Result
Random Errors	Ederington (1986)	U.S. industrial bonds	Moody's; S&P	493 bonds; 1975 to 1980	No systematic differences between two CRAs. Split ratings are due to merely random error.
	Jewell and Livingston (1998)	U.S. industrial bond	Moody's; S&P	1,277 bonds; 1980 to 1993	The yield for split rated bonds is priced at an average of the two ratings.
	Cantor and Parker (1996a)	Sovereign	Moody's; S&P	49 countries, 1995	No systematic differences between CRAs. Split rating is due to the difficulty of assessing sovereign credit risk and the relative youth of CRAs in this area
Heterogeneity of determinants and methodology	Moon and Stotsky (1993)	Municipal bond	Moody's; S&P	892 municipalities; 1981	Two CRAs have different ways to classify bond as well as put weight to the important determinants
	Pottier and Sommer (1999)	Individual property-liability insurers	Best; S&P; Moody's	1678 insurers; 1996	Rating CRAs use an identical set of determinants and weight those determinants differently
	Livingston et al. (2010)	U.S. domestic, nonfinancial bond issues	Moody's; S&P	13,853 bonds; 1983 to 2008	There is indeed a systematic difference between the two rating CRAs and bond investors pay more attention to the information opaqueness.
	Alsakka and ap Gwilym (2012a)	Sovereign	Moody's; S&P; Fitch; CI; R&I; JCR	49 emerging countries; 2000 to 2008	CRAs use different economic factors and weight them differently
Information opacity	Morgan (2002)	Bank bonds	Moody's; S&P	1983 to 1993	Disagreement over bank ratings is the result of asset opacity
	Livingston and Naranjo (2007)	U.S. bond issues	Moody's; S&P	3,213 bonds; 1983 to 2000	Split rating is likely to occur to firms with asset opaqueness problems
	Livingston et al. (2008)	U.S. bond issues	Moody's; S&P	9,431 bonds; 1983 to 2000	Two ratings remain their relative position over time, hence, random errors are not the cause
	Livingston et al. (2010)	U.S. domestic, nonfinancial bond issues	Moody's; S&P	13,853 bonds; 1983 to 2008	There are indeed systematic differences between the two CRAs and bond investors pay more attention to the information opaqueness.
	Livingston and Zhou (2010)	U.S. bond issues	Moody's; S&P	14,005 bonds, 1983 to Sep 2008	Split ratings are signal of the information opacity and investor price that risk into bond yields.
	Alsakka and ap Gwilym (2012a)	Sovereign	Moody's; S&P; Fitch; CI; R&I; JCR	49 emerging countries; 2000 to 2008	Opaqueness countries are harder to evaluate and hence, CRAs tend to give different opinions about them.
Solicited vs unsolicited ratings	Poon et al. (2009)	Commercial banks	S&P	460 commercial banks in 72 countries (excluding the U.S.)	The differences in ratings of commercial banks can be explained by the solicitation status and financial characteristics.

Table 2.3. Continued

Common cause	Study	Type of data	CRAs	Sample size	Result
Home region bias	Alsakka and ap Gwilym (2010)	Sovereign	Moody’s; S&P; Fitch; CI; R&I; JCR	49 emerging countries; 2000 to 2008	CRAs give favourable ratings to countries they are operating in because of better knowledge.
	Alsakka and ap Gwilym (2012b)	Sovereign	Moody’s; S&P; Fitch; CI; R&I; JCR	49 emerging countries; 2000 to 2008	CRAs operating in the same region or areas might give higher ratings to a country because of their better understanding of that specific area or region.
	Shin and Moore (2003)	Japanese corporates	Moody’s; S&P; R&I; JCR	92 Japanese firms	Japanese CRAs tend to assign higher ratings to the home country firms than the U.S. CRAs.
Corporate-specific cause	**Study**	**Type of data**	**CRAs**	**Sample size**	**Result**
Heterogeneity of rating categories	Cantor and Packer (1996b)	U.S. corporations	Moody’s; S&P; Duff & Phelps and Fitch	871 companies; year-end 1993	There is systematic heterogeneity in rating scales across CRAs.
	Cantor and Packer (1997)	U.S. corporations	Moody’s; S&P	1,137 companies, 1993	Rating differences represent the differences in rating scales of CRAs.
	Dandapani and Lawrence (2007)	Hypothetical grading scales	None	Using two hypothetical grading scales on two university	One-third of bond split rating can be explained by the heterogeneity of the rating scales
	Livingston et al. (2008)	U.S. bond issues	Moody’s; S&P	9,431 bonds; 1983 to 2000	Two ratings remain their relative position over time, hence, random errors are not the cause
Influence of large shareholders	Kedia et al. (2017)	U.S. new bond issues	Moody’s; S&P	9,550 bonds; 2001 to 2010	Moody’s are higher than S&P for bonds issued by firms invested by Moody’s large shareholders.
Sovereign-specific cause	**Study**	**Type of data**	**CRAs**	**Sample size**	**Result**
Political risk and transparency	Vu et al. (2017)	Sovereign	Moody’s; S&P; Fitch	64 countries, 1997 to 2011	Countries have a week economy and bad political risk tend to receive different opinions from CRAs.

Note: Table 2.3 presents the summary of previous literature (both corporate and sovereign) on the causes of split ratings.

Chapter 3: Split ratings and the cost of equity capital

3.1 Introduction

Credit rating agencies (CRAs) are important players in the financial markets. They address the information asymmetries between investors and corporations by assessing the creditworthiness of issues or issuers. Firms' decision regarding capital structure, debt structure (bank debt versus nonbank debt) and investments are significantly affected by credit ratings (see, for example, Kisgen, 2006; 2009; Harford and Uysal, 2014; Jory et al., 2016; Bedendo and Siming, 2018). Following the U.S. subprime mortgage crisis, many questions have been raised on the performance of CRAs' assessments. CRAs have been criticized by policymakers, investors and financial analysts for their failure to foresee high profile default events such as: Enron, WorldCom, Lehman Brothers and mortgage-backed securities. Furthermore, the heavy usage of credit ratings in various banking and investment regulations contribute to the impact of CRAs on financial markets (Becker and Milbourn, 2011). Nevertheless, ratings from different CRAs are often treated as being equal to each other. This common practice may be applicable if firms only solicit one rating from one CRA. However, almost all large and liquid U.S. corporate bonds have multiple ratings from Moody's and S&P (Bongearts et al., 2012) because doing so should maximize their potential for accessing funds (known as the "two rating norm" (Mahlmann, 2009)). Since multiple ratings are common in the U.S., important research questions arise when CRAs disagree with each other regarding issues' or issuers' credit ratings. The key aim of this Chapter is to investigate the impact of CRAs' disagreement over firms' creditworthiness on firms' cost of equity capital. This Chapter focuses on two research questions: (i) whether split ratings have any impact on firms' cost of equity capital and (ii) whether superior ratings from one CRA have a different impact on firms' cost of equity capital than superior ratings from the other.

This Chapter seeks to contribute new insights to this research theme in two respects. First, it investigates the impact of split ratings on the equity markets. Second, it examines the effects of split ratings with superior Moody's and split ratings with superior S&P ratings on firms' cost of equity. Credit ratings convey valuable information to the equity markets (Badoer and Demiroglu, 2018) and thus, split ratings might bring new information to the equity market like they do in the debt markets (see., Livingston et al., 2010; Drago and Gallo, 2018). However, since equity investors and debt investors have different opinions toward firms' credit risk, understanding the relationship between split ratings and cost of equity capital will shed some light on the perception of equity investors regarding split ratings and their preferences for soliciting CRAs. Previous split ratings literature finds that CRAs disagreement over firms' credit ratings could have a significant economic impact. Livingston et al. (2010) and Livingston and Zhou (2010) find that split ratings do have an impact on bond yields. Indeed, bond yields are higher if bond issues received different ratings from CRAs. Livingston et al., (2010) also find that bond investors differentiate between two CRAs, Moody's and S&P. Investors place more weight on Moody's ratings, the more conservative CRA, when there are disagreements between these two CRAs.

Multiple ratings contribute additional important information to the markets. Additional ratings can potentially reduce the information asymmetry surrounding firms' creditworthiness and thus, produce a benefit for firms as well as investors. However, when it comes to credit risk assessments, bond investors tend to require a higher borrowing cost for bonds with split ratings versus non-split rated bonds (Livingston et al., 2010). Livingston et al. (2010) argue that firms with split ratings are more likely to have higher information opacity problems and consequently higher information asymmetry between firms and investors. Thus, split-rated firms are subjected to more uncertainty surrounding their true credit risk than non-split rated firms. Given that equity investors are sensitive towards uncertainty and information asymmetry problems, one could expect equity investors to require a higher cost of equity capital on split-rated firms.

In order to answer the question of whether or not split ratings have any impact on the cost of equity capital, this Chapter employs a sample of all U.S. corporations rated by both Moody's and S&P from 2003 to 2017. Split ratings in this Chapter are defined as the annual average of daily split at rating/outlook/watch status. This setup is able to capture the full picture of the two CRAs' credit opinions. Furthermore, for the dependent variables, following Li and Mohanram (2014), a cross-sectional regression model is implemented to generate the earnings forecasts, which in turn are used the various cost of capital models to capture the required rate of return/cost of equity capital.

The first main finding of the study is that split ratings have a significant impact on the cost of equity capital. A disagreement of one rating notch leads to about 42 basis point of 'premium' on the cost of equity capital of split rated firms compared to that of their non-split rated peers. Equity investors appear to recognize the disagreement between two CRAs and take it into consideration when assessing the cost of equity capital. This finding supports earlier studies which report that investors differentiate between CRAs and split ratings have economic impacts on firms (Livingston et al., 2008; Livingston et al., 2010). To rule out endogeneity concerns, propensity score matching is employed with various matching techniques. The results from the matched samples are consistent with the main results.

Second, when Moody's has superior ratings, equity investors require a higher cost of equity capital for split rated firms compared to when S&P has superior ratings. This finding is in contrast with Livingston et al. (2010) in relation to how bond investors respond to split ratings between Moody's and S&P. This distinctive perspective of the two types of investors about split ratings is the result of the different relationship of these two investors (i.e. bond versus equity) with the firms. While bond investors are creditors of the firms, equity investors are the owners of firms. The differences in the nature of the relationship between bond and equity investors and the corporates explain why these two types of investors have potentially opposite interpretations when split ratings occur. Since equity investors bear higher risk than bond investors with fixed income investments, they are more sensitive toward information asymmetry than the bond investor counterparts. Hence, their reaction toward the ambiguity of CRAs about firms' creditworthiness is more drastic than bond investors.

The findings in this Chapter suggest that firms can benefit from addressing any ambiguity that makes split ratings more likely. Firms can employ high-quality accounting disclosure to reduce information opacity, which in turn lessens the chances of CRAs' disagreement and therefore can significantly diminish the premium that they have to pay if they receive split ratings. In addition, the study finds that credit ratings from the two major CRAs are not equivalent to each other and equity investors recognize these differences, suggesting there is indeed some systematic differences between S&P and Moody's.

This Chapter is organized as follows. Section 3.2 reviews related literature. Section 3.3 explains the research hypotheses. Section 3.4 describes the research methodologies. Section 3.5 details the dependent, independent and control variables used as well as the sample selection and descriptive statistics. Section 3.6 presents the empirical results. Section 3.7 explores some robustness tests and Section 3.8 concludes the Chapter.

3.2 Literature review

In the U.S. rating market, there are only 10 Nationally Recognized Statistical Rating Organizations (NRSROs) (see Chapter 2 for more details). Moody's and S&P control for

75.1% of corporate ratings market share (SEC, 2017).[10] In an efficient market environment, one rating should be sufficient enough to fulfil the information functions. However, in the U.S., corporations usually solicit ratings from more than one CRA. In fact, almost all large and liquid corporation bonds are rated by Moody's and S&P (Bongaerts et al., 2012). Thus, the question of why firms need multiple ratings is one of the main investigations of the recent credit rating literature.

Bongaerts et al. (2012) suggest three hypotheses of why firms solicit multiple ratings: i) information production; ii) rating shopping and iii) regulatory certification. The information production hypothesis suggests that firms seek additional ratings to reduce the information asymmetry between firms and investors. Extra ratings reduce the uncertainty surrounding firms' creditworthiness and would help firms to maximize their access to the capital market (Mahlmann, 2009). Furthermore, firms with multiple ratings could also have a lower borrowing cost benefit from extra information as banks, on average, apply lower syndicated loan spreads to multi-rated firms (Drago and Gallo, 2018). Securities of firms, who receive similar ratings from different CRAs, are less likely to suffer from opaqueness problem, thus, more likely to have their true evaluation and more likely to secure the best possible price (Baker and Mansi, 2002). The rating shopping hypothesis suggests that issuers can decide to "shop" for better ratings (Skreta and Veldkamp, 2009; Bolton et al., 2012). Issuers can approach different CRAs but then choose to report only the most favourable ratings (Drago and Gallo, 2018). This issue is a common criticism of the issuer-pays model, which most of major CRAs apply (Kashyap and Kovrijnykh, 2016). Regulatory certification hypothesis implies that firms seek additional ratings to achieve a certain rating classification. Since market and regulator separate bonds into two different types: informationally sensitive (speculative-grade) and non-informationally sensitive (investment-grade), firms are driven to reach the non-informationally sensitive boundary to maximize their access to credit and financial markets. Bongaerts et al. (2012) find that firms whose Moody's and S&P ratings are on opposite sides of the investment-grade boundary are more likely to reach investment-grade classification if Fitch assigns them favourable ratings.

Previous studies find mixed results on the impact of increasing competition in the rating markets. Some studies find that the expansion of the number of NRSROs have a positive impact on rating accuracy (Behr et al., 2016) while the others argue that increased competition reduces

[10] Moody's and S&P also account for 62% of financial institutions', 46.1% of insurance companies', 64.7% of asset-backed securities' and 88% of government securities' credit ratings.

the quality of ratings (Becker and Milbourn, 2011; Dimitrov et al., 2015). Another line of argument about multiple ratings, "rating shopping" in particular, is the issuer-pay model. Kashyap and Kovrijnykh (2016) find that investors-pay model produces less rating errors than the issuer-pay model. They further argue that competition for market share leads to less accurate ratings.

The existing literature about split ratings has pointed out a number of reasons that split ratings could occur. First, split ratings are the result of a random error occurring during the evaluating process because such process is difficult and sophisticated (Ederington, 1986). This random hypothesis suggests that investors will recognize that the disagreement among CRAs is just merely random error and non-systematic; hence, the yield on split rated bonds should be the same as non-split rated bonds of similar credit risk. Second, split ratings are the results of systematic differences among CRAs. These systematic differences could be differences in rating determinants (Moon and Stotsky, 1993), differences in methodologies or differences in weight put on determinants (Pottier and Sommer, 1999). Under this hypothesis, the yield on split rated bonds should be different than the yield of non-split rated bonds of similar credit risk because of the systematic differences among CRAs. Finally, asset opacity is one possible reason that CRAs give different ratings to the same issues/issuers (Morgan, 2002). Under this hypothesis, if opacity problems exist, conservative CRA, who is more relatively worry about overrating than about too pessimistic evaluations, tend to assign less favourable ratings than other CRAs. Many studies have documented that Moody's are more conservative than S&P on corporate ratings (Livingston et al., 2008; Livingston et al., 2010). Bond investors are concerned about rating inflations and hence rely heavily on more conservative CRAs. However, Cantor et al. (2007) find that rating accuracy is more important to investors than rating stability. In addition, split ratings could be the results of the influence of large shareholders of CRAs. Kedia et al. (2017) find that Moody's are less objective when it comes to firms invested by the two stable large shareholders of Moody's (Berkshire Hathaway and Davis Selected Advisors). They find that Moody's ratings are about 0.467 notches higher than S&P for those bonds. Kedia et al. (2017) suggest that the way that large shareholders could exert such influence on CRAs is through the threat of exit and voice.

An implication of the second and third hypotheses on the existence of split ratings is that if investors differentiate between two CRAs, the yields of bonds with superior rating from conservative CRA should be different from the yields of bonds with superior ratings from generous CRA. However, the split rating literature gives an inconsistent conclusion about the impact of split ratings on bond yields. Some studies find that bond yields are set by either inferior ratings (Liu and Moore, 1987; Perry et al., 1988) or superior ratings (Hsueh and Kidwell, 1988). Cantor et al. (1997) and Jewell and Livingston (1998) find that both superior and inferior ratings help to set the bond yields. Livingston and Zhou (2010) and Livingston et al. (2010) also find that yield on split rated bonds and similar credit risk non-split rated bonds are about 7 basis point apart. Consistent with Livingston et al. (2010), Drago and Gallo (2018) also find that the greater the rating dispersion, the higher borrowing cost (in terms of syndicated loan spreads). Furthermore, Livingston and Zhou (2016) find that information-opaque bonds' yield premiums are lower by about 15 basis points when firms solicit Fitch ratings in addition to ratings from Moody's and S&P. They suggest that additional information from Fitch ratings can reduce the opacity premium. In addition, high-quality accounting disclosure is also a mechanism to reduce information opacity and reduce the impact of information opaqueness to bond yield spreads (see Sengupta, 1998; Yu, 2005).

Hence, all the existing literature about split ratings focus on bond yields and none of the prior literature has considered the impact of split ratings on the cost of equity counterpart. Understanding this relation is very important because split ratings could convey more information to the market. Split ratings could be the signal of the uncertainty surrounding firms' creditworthiness and it could have a significant economic impact on firms' cost of equity capital. Thus, this relationship could also have a potential effect on firms' investment and financial decisions. Equity investors could recognize this relationship and differentiate between two situations, split rated and non-split rated. Moreover, many studies have investigated the preference of bonds investors towards the two major CRAs and found that bond investors are more concerned about the rating inflation and put more weight on more conservative CRAs while assessing credit risk. However, no empirical studies have looked into the perception of equity investors (as the firms' owner/shareholders) towards the two major CRAs. Gaining knowledge on this relationship could shed a light on the reliance of equity investors on credit ratings and contribute to the argument that regulators should increase the monitoring and evaluating of the performance of CRAs and should not treat CRAs as equal.

3.3 Research hypotheses

Given the practical importance and relevance of the impact of split ratings and the gap in the existing literature, two hypotheses are proposed:

Hypothesis 1: Split ratings do not have any impact on the cost of equity capital.

The null Hypothesis 1 is tested against the alternative hypothesis that equity investors recognize the different opinions of CRAs on corporate issuers' creditworthiness and they also demand a risk premium to reflect the inherent ambiguity of split ratings. If the null hypothesis is rejected, it is suggested that equity investors are aware of the disagreement between CRAs upon firms' creditworthiness and act accordingly. If the rating dispersion is short-lived (temporary), it could be the results of differences in timing between CRAs. However, if the disagreement lasts longer (permanent split), it could represent some fundamental differences between CRAs. Since the disagreement upon credit ratings is the sign of ambiguity about the firms' information opacity problem, equity investors are expected to charge a premium to compensate for the extra uncertainty. This means that firms with split ratings have to pay a higher cost of equity capital than non-split rated firms with similar credit risk. The ambiguity or uncertainty of CRAs about the creditworthiness of issuers could be the result of asset opaqueness (see, Morgan, 2002; Livingston et al., 2010). Equity investors should consider split ratings as a sign of greater information asymmetry between firms and investors. It has been reported that the greater the information asymmetry, the higher the financing cost of capital (Botosan and Plumlee, 2002; Hughes et al., 2007). Equity investors are expected to be sophisticated, recognize and charge a premium for the uncertainty about firms' credit risk portrayed by split ratings. In order to test Hypothesis 1, it is essential to calculate the cost of equity capital and split ratings. The cost of equity capital is calculated using the implied cost of capital (ICC) approaches together with the cross-sectional regression forecast model (see Section 3.4.4).

Hypothesis 2: Superior ratings from Moody's have a different impact on the cost of equity capital than superior ratings from S&P.

To test Hypothesis 1, absolute split ratings are used, meaning that the hypothesis does not test whether superior ratings from one CRA have a different impact than superior ratings from another CRA. However, Hypothesis 2 investigates the individual impact of superior/inferior ratings from a given CRA on the cost of equity capital when split ratings occur. The null hypothesis is tested against the alternative hypothesis that investors perceive CRAs differently and assign different weigh toward their ratings in the cost of equity capital evaluating process. If the null hypothesis is rejected, the conclusion is that investors give different weights to CRAs when assessing the cost of equity capital and thus, consider one CRA more reliable than the other. Because the equity investors are sophisticated, and hence differentiate between CRAs, the null hypothesis is expected to be rejected. Furthermore, as the nature of the relationship between equity investors and rated issuers is ownership relationship, equity investors preference of CRAs is expected to be different compared to bond investors. Bond investors put more weight on more conservative CRAs since their attitude towards risk are more likely to be risk averse. Thus, they are more concerned about rating inflation and assign more weight to CRA with lower ratings. However, given that equity investors are the owner of issuers, they might prefer a more generous CRA than a more conservative CRA. Thus, equity investors might place more emphasis on S&P ratings when assessing firms' cost of equity capital as S&P is a more generous CRA compared to Moody's.

3.4 Research design

To present evidence relating to the two Hypotheses, a multivariate regression model is used to examine the relationship between split rating and the cost of equity capital.

3.4.1 Split ratings and the cost of equity capital

$$COEC_{i,t} = \beta_0 + \beta_1 ASPLIT_{i,t} + \gamma_j \sum_{j=1}^{n} CONTROL_{i,j,t} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t} + \varphi_l \sum_{l=1}^{15} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \quad (3.1)$$

COEC$_{i,t}$: the annual cost of equity capital of firm i at year t, calculated as the average of four ICC measures. (see Section 3.4.3 for the detailed description of the cost of equity capital 'COEC')

ASPLIT$_{i,t}$: the rounded absolute time-weighted split ratings between Moody's and S&P of firm *i* at year *t*. This variable is to capture the impact of rating differences upon *COEC* (See Section 3.4.4 for detailed description of split ratings).

CONTROL$_{,i,t}$: set of *n* (6) control variables of firm *i* at year *t* (see Section 3.4.5 for the full list of control variables).

$LEVEL_{i,t}$: is a set of 19 dummy variables representing the rating level based on the 20-notch rating scale of firm i at year t.[11] The dummy variables are equal to 1 if the average ratings of the two CRAs belong to that group and 0 otherwise. The base case in this model is the 20th group which is the highest possible rating level (AAA/Aaa).

YEAR×*INDUSTRY*: is the year*industry interaction terms, where *YEAR* is a series of 15 (*l*) dummy variables to control for the year effect and *INDUSTRY* is a series of 8 (*m*) dummy variable to control for the industry effect.[12]

Eq. (3.1) examines the impact of split rating regardless of which CRA assigns the superior (inferior) ratings to that issuer. If split ratings have an impact on the cost of equity capital, β_1 will be positive and significant.

In addition to the baseline model, three different cross-sectional models are tested to investigate the effect of different firm's size (large firms vs small firms), different rating levels (investment-grade firms vs speculative-grade firms) and different time period (crisis vs pre/post-crisis).

3.4.2 Superior Moody's, Superior S&P and the cost of equity capital.

The question can be interpreted as whether the impact of split ratings when CRA1 (e.g. Moody's) assigns a superior rating is the same as the impact when CRA2 (e.g. S&P) assigns the superior rating. In order to answer this question, two dummy variables (*SUP_MOODY* and *SUP_S&P*), which indicates the superior rating from Moody's or S&P in the pair, are added to Eq. (3.1) to separate the impact of superior rating from each CRA to the other. Thus, in this specification, the non-split rated firms are the base case.

$$
\begin{aligned}
COEC_{i,t} = \beta_0 + \beta_1 SUP\_MOODY_{i,t} + \beta_2 SUP\_S\&P_{i,t} \\
+ \gamma_j \sum_{j=1}^{n} CONTROL_{i,j,t} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t} \\
+ \varphi_l \sum_{l=1}^{15} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t}
\end{aligned}
\tag{3.2}
$$

[11] The 20-unit rating scale is used instead of the 58-unit CCR scale to reduce the number of dummy variables included and preserve the model's degrees of freedom (see Section 2.3.1 and Table 2.2 for rating scale definition).
[12] *INDUSTRY* is defined using the first digit of the SIC codes.

where $SUP\_MOODY_{i,t}$ ($SUP\_S\&P_{i,t}$) is a dummy variable equal to 1 if Moody's (S&P) ratings are superior compare with S&P (Moody's) and 0, otherwise. *CONTROL*, *LEVEL* and *YEAR×INDUSTRY* definitions are similar as in Hypothesis 1.

The coefficient β_1 (β_2) of $SUP\_MOODY_{i,t}$ ($SUP\_S\&P_{i,t}$) in Eq. (3.2) represents the differences between COEC when a split rated bond issuer has a superior rating from Moody's (S&P) compare to non-split rated firms.

Thus, if CRAs are treated by investors as equivalent to each other, meaning the effect of superior rating from one CRA is similar to the effect of superior rating from the other, the coefficients on $SUP\_MOODY_{i,t}$ and $SUP\_S\&P_{i,t}$, β_1 and β_2, should be insignificantly different from each other (or the null hypothesis that $\beta_1 = \beta_2$ cannot be rejected).[13] However, if the null hypothesis is rejected or β_1 and β_2 are significantly different from each other, then the COEC for firms with a superior rating from Moody's is significantly higher (lower) than for firms with a superior rating from S&P.

In addition to dummy variables for superior ratings, two more variables ($SUP\_MOODY\_CCR_{i,t}$ and $SUP\_S\&P\_CCR_{i,t}$) are added to examine the impact of the size of the split. Wider splits are expected to result in a stronger impact on the COEC. Thus, the specifications to test this is presented as follows:

$$\begin{aligned} COEC_{i,t} = {} & \beta_0 + \beta_1 SUP\_MOODY\_CCR_{i,t} + \beta_2 SUP\_S\&P\_CCR_{i,t} \\ & + \gamma_j \sum_{j=1}^{n} CONTROL_{i,j,t} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t} \\ & + \varphi_l \sum_{l=1}^{15} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \end{aligned} \tag{3.3}$$

where $SUP\_MOODY\_CCR_{i,t}$ ($SUP\_S\&P\_CCR_{i,t}$) is a variable equal to $SPLIT_{i,t}$ if Moody's (S&P) ratings are superior compare with S&P (Moody's) and 0 otherwise. *CONTROL*, *LEVEL* and *YEAR×INDUSTRY* definitions are similar as in Hypothesis 1.

3.4.3 Dependent variable – the cost of equity capital (COEC)

The cost of equity capital is the main dependent variable in all regression models. There are numerous methods used in the literature to calculate this cost. The traditional method is to

[13] The equality of the two regression coefficients could be assessed by an F-test.

use historically observable data to estimate the cost of equity, whereby the two famous models for this method are the market model and the Capital Asset Pricing Model (CAPM). However, the problem of these models is that they use realized returns to infer the cost of equity and that there is a weak correlation between realized returns and expected returns (Elton, 1999). In addition, there is non-existent relationship between realized returns and measure of risk. For instance, Fama and French (1992) show that there is no convincing evidence of the relationship between market beta and the average realized returns and that the usefulness of historically observable approaches is limited.

In order to overcome the problems with using historical data, researchers have developed the ICC approaches. The basic idea of these approaches is to calculate the cost of equity capital as the internal rate of return in a valuation model. The most popular approach to calculate ICC is to use the analysts' forecast as a proxy to the forecasted earnings. However, analysts' forecasts are limited or unavailable for a subset of U.S. firms (small and financial distressed firms) and almost half of all firms do not have coverage in most years (Li and Mohanram, 2014). Furthermore, Easton and Monahan (2005) show that analysts' forecasts have weak correlations with future returns and they are not a reliable proxy for expected returns.

Another approach that addresses these shortcomings is using cross-sectional regressions to generate earnings forecasts and then using these earnings forecasts to compute the ICC estimations. Recent literature shows that model-based ICC outperform the analyst-based ICC (Hou et al, 2012; Li and Mohanram, 2014) and thus, it has been used in many studies (e.g., Chang et al., 2012; Jones and Tuzel, 2013; Li and Mohanram, 2014). The implementation in this Chapter follows from Li and Mohanram (2014), whose model has been demonstrated to outperform the original cross-sectional model of Hou et al. (2012) in terms of forecast accuracy, bias, earnings response coefficients (ERC) and correlations of ICC with future returns and risk factors.[14]

3.4.3.1 The RI cross-sectional model:

$$E_{i,t+\tau} = \beta_0 + \beta_1 E_{i,t} + \beta_2 NE_{i,t} + \beta_3 E_{i,t} NE_{i,t} + \beta_4 B_{i,t} + \beta_2 TAC_{i,t} + \varepsilon_{i,t+\tau} \qquad (3.4)$$

where

$E_{i,t+\tau}$ is earnings of firm *i* in year $t+\tau$ divided by number of shares outstanding in year *t*.

[14] ERC measure the correlation between forecast surprise and future abnormal returns (Li and Mohanram, 2014)

$NE_{i,t}$ is dummy variable taking the value of 1 if firm *i* in year *t* has negative earnings and zero otherwise

$E_{i,t}NE_{i,t}$ is the interaction term between NE and E of firm *i* in year *t.*

$B_{i,t}$ is the book value per share of firm *i* in year *t.*

$TAC_{i,t}$ is the total accruals of firm *i* in year *t*, calculated using Richardson et al.'s (2005) method, which is the sum of the change in non-cash working capital, the change in net non-current operating assets and the change in net financial assets, divided by number of shares outstanding. TAC = ΔWC + ΔNCO + ΔFIN, where WC is estimated as the differences between Current Operating Assets (COA) – Current Operating Liabilities (COL), COA = Current Asset (Compustat item: *act*) – Cash and Short-Term Investment (*che*), while COL = Current Liabilities (*lct*) – Debt in Current Liabilities (*dlc*). NCO = Non-Current Operating Assets (NCOA) – Non-Current Operating Liabilities (NCOL), NCOA = Total Asset (*at*)– Current Assets (*act*) – Investment and Advances (*ivao*), NCOL = Total Liabilities (*lt*) – Current Liabilities (*lct*) – Long-Term Debt (*dltt*). FIN = Financial Assets (FA) – Financial Liabilities (FIL), FA = Short Term Investments (*ivst*) + Long Term Investment (*ivao*), FIL = Long Term Debt (*dltt*) + Debt in Current Liabilities (*dlc*) + Preferred Stock (*pstk*). Missing values of TAC are set to be zero (Li and Mohanram, 2014). However, this restriction will be relaxed as a robustness test to the model.

The cross-sectional models give the earnings forecasts for year *t + 1* to year *t + 5*. For each year in the data set, predicted earnings for year *t + 1* to *t + 5* are estimated using the pooled regression with all available observation for the past 10 years (year *t – 1* to year *t – 10*). For instance, if 2010 is the year t, all available data from 2000 (*t – 10*) to 2009 (*t – 1*) is used to calculate the coefficients for the year t+1 forecasted earnings model. The forecasted earnings of 2011 (*t + 1*) are obtained by multiply these coefficients with the independent variables of year 2010 (*t*). Similarly, all available data from 1999 to 2008 is used to estimate the forecasted earnings of year 2012 (*t + 2*). This method is to make sure the data used to estimate the forecast are not in the data set used to estimate these models' coefficients (Li and Mohanram, 2014). Another advantage of using this method is that it allows the survivorship bias to be minimum as only non-missing independent variable in year t is required to estimate future earnings.

The earnings forecasts (forwarded earnings per share - EPS) generated from the cross-sectional model in Eq. (3.4) then are used as inputs to 4 ICC metrics (OJ, PEG, GLS and CT) to estimate the COEC for firms. As the common approach in the ICC literature (e.g. Hou et al.

2012; Li and Mohanram, 2014), the average of the four aforementioned ICC approaches is used as the COEC in this Chapter.

3.4.3.2 Computing implied cost of capital.

The earnings forecasts generated from the cross-sectional regression model Eq. (3.4) are used to compute ICC. Four common metrics, GLS (Gebhardt et al., 2001), CT (Claus and Thomas, 2001), OJ (Ohlson and Juettner-Nautoth, 2005) and PEG (Easton, 2004) are used and COEC is computed as the average of the four estimates (Hou et al, 2012; Li and Mohanram, 2014). The average COEC will be calculated based on the available ICC measures if there are missing observations on any of these ICC measures.

OJ model (Ohlson and Juettner-Nautoth, 2005)

$$R_E^{OJ} = A + \sqrt{A^2 + \frac{E_1}{P_0}(g_2 - (\gamma - 1))} \tag{3.5}$$

where $A = 1/2 \times ((\gamma - 1) + D_1/P_0)$, $g_2 = (E_2 - E_1)/E_1$, R_E^{OJ} is the firm cost of equity capital, E_t is the forecasted earnings per share at time *t*, $P_0$is the firm current price, and D_t is the dividend on year *t*. Following Gode and Mohanram (2003), the $(\gamma - 1)$ is set to be equal to r_f – 3%, where r_f is the risk-free rate, which is set as the 10-year U.S. Treasury Bond rate. g_2 is the geometric mean of the short term growth $((E_2 - E_1)/E_1)$ and the long-term growth rate $(\sqrt[4]{E_5/E_1} - 1)$ if the long-term growth rate is less than the short-term growth rate. Otherwise, $g_2$is set as the long-term growth rate. Current dividend pay-out is computed as dividends divided by income before extraordinary items (IB) for firms with positive earnings and equal to dividends divided by 6% of total assets for firms with negative earnings. The future pay-out will be set to be equal as current pay-out. Dividend on year *t* is computed as dividend pay-out times earnings per share on year *t*.

The OJ model (Ohlson and Juettner-Nautoth, 2005) is constructed under the two-year horizon and assumptions regarding the growth in abnormal earning ($A > 0$), the abnormal earning growth ($g_2 > 0$) and the dividend ($D_t > 0$) (Li and Mohanram, 2014).

PEG model (Easton, 2004)

PEG model is the simplified version of the OJ model (Ohlson and Juettner-Nautoth, 2005), where dividends are ignored.

$$R_E^{PEG} = \sqrt{\frac{g_2}{(P_0/E_1)}} \tag{3.6}$$

where E_t, P_0 and g_2 are defined similarly to the OJ model. In this special case, when the time horizon is 2, the growth in abnormal earnings is 0 and there is no dividend pay-out, the abnormal growth model (OJ model) is reduced to a simplified version called the price-earning-to-growth ratio (PEG ratio) (Li and Mohanram, 2014).

GLS model (Gebhardt et al., 2001)

Instead of the abnormal growth model such as OJ and PEG models, the GLS model suggested by Gebhardt et al. (2001) uses the residual income model (RIM) to calculate the cost of equity capital. This model separates the detailed-plan horizon in the RIM model into two stages. The first stage is forecasting the earnings for the next five years by using RIM and the forecasted earnings per share obtained from the RI model in Section 3.4.3.1. In the second stage, the median industry return on equity (ROE^{ind}) then is used to calculate the return on equity from year six to year eleven: $ROE_t = 1/6 \times \left(ROE^{ind} - ROE_{t-1}\right) + ROE_{t-1}$ for year 6,…,11. The forecasted earnings per share and book value per share for this period then will be derived from the clean surplus relation: $B_{t+1} = B_t + ROE_t - D_t$. Similar to the OJ model, pay-out is set to equal current pay-out, which is defined as dividends divided by IB for firms with positive IB or dividends divided by 6% of total assets. With this approach, the abnormal return on equity over time is captured with the assumption that in the long run, the return of individual firms tends to become similar to their industry return (Gebhardt et al., 2001).

$$P_0 = B_0 + \sum_{t=1}^{12} \frac{E_t - R_E^{GLS} \times B_{t-1}}{(1 + R_E^{GLS})^t} + + \frac{(E_{12} - R_E^{GLS} \times B_{11})}{(1 + R_E^{GLS})^{12} R_E^{GLS}} \tag{3.7}$$

where E_t is the forecasted earnings per share at time *t* (obtained from the RI model for the first five years and inferred from expected ROE and lagged book value per share for year 6 to year 11), B_t is book value per share at time *t* and $P_0$is the firm current price per share.

The GLS model also relies on the assumptions that the detailed-plan horizon is fixed for all firms. Consequently, the fixed horizon plan and firms’ state of grows sometimes conflict, for instance, if the fixed horizon is too short (long) for mature (young) firms, the implied risk premium would be underestimated (overestimated) for mature (young) firms (Gebhardt et al., 2001). Another assumption that could lead to bias in the GLS model is considering the median

ROE of the industry as the firms' ROE in the long run, one might argue that certain kinds of firms need to be treated specially (Gebhardt et al., 2001). For example, a market leader in a well-protected niche market deserves a higher target ROE than industry ROE.

CT model (Claus and Thomas, 2001)

Similar to GLS, the CT model also uses RIM to estimate ICC. However, instead of using 12-year-plan horizon like GLS, CT model only uses a 5-year-plan horizon and after the plan horizon, the earnings growth rate is set to be the rate of inflation.

$$P_0 = B_0 + \sum_{t=1}^{5} \frac{E_t - R_E^{CT} \times B_{t-1}}{(1 + R_E^{CT})^t} + \frac{(E_5 - R_E^{CT} \times B_4)(1 + g)}{(1 + R_E^{CT})^5 (R_E^{CT} - g)} \quad (3.8)$$

where g is firm's long-term growth rate and set to r_f – 3%. Similar to the GLS model, the CT model also subjects to the assumption regarding the detail-plan horizon and in this case is 5 years, the dividend pay-out ratio and the growth rate.

Table 3.1 details all four ICC metrics used in this Chapter to calculate the COEC by using the forecasted earnings per share generated from the RI model.

3.4.4 Split ratings

In order to test this Chapter hypotheses, the key independent variable (the split ratings variable) needs to be defined. Type of ratings are used to generate split ratings is the long-term foreign currency credit ratings for S&P and long-term issuer credit ratings for Moody's. In the previous literature, there are two different numerical rating scales that are used: the conventional numerical scale - which ranges from 1 to 18, 20 or 22 (Livingston et al., 2008; Alsakka and ap Gwilym, 2009, 2010; Livingston et al., 2010); and the comprehensive credit rating (CCR) numerical scale - which ranges from 1 to 58 (See Section 2.3.1 for more details on the two rating scales). In this Chapter, the CCR numerical scale is used because it shows the full picture of credit ratings from CRAs. The key independent variable (*ASPLIT*) is then defined as the rounded average of absolute daily differences between Moody's and S&P ratings (the direction of the split used is (Moody's – S&P)) over each firms' fiscal year. Split ratings are then rounded to the nearest integer to remove the effect of short-lived splits. Because CRAs have different time duration for processing new information, different time intervals for reviewing ratings, and different rating policies (rating stability versus rating accuracy), the timing of rating actions across CRAs normally differs. Therefore, a short-lived split between CRAs might just represent the differences in the timing of their actions rather than represent fundamental changes in CRAs' opinions on firms' creditworthiness. By using the rounded split, the effect of minor differences in the timing of actions is reduced (one CCR unit split for less than 6 months will be removed effectively by rounding). In addition, more-than-4-CCR units splits are grouped into the 4-CCR units categories because large splits are uncommon.

Previous literature on split ratings (e.g., Livingston and Zhou, 2010; Livingston et al., 2010) use samples based on new bond issues. This is because split ratings on existing bond issues could be the outcome of a timing mismatch between the two CRAs (e.g., one CRAs might be slower in updating its ratings compared to the other CRA and that might not be a genuine signal of information asymmetry). However, due to the nature of the measurement of dependent variables in this Chapter (i.e., the cost of equity capital), which rely on balance sheet values, the thesis measures split ratings using existing issuer ratings. Thus, the split ratings in this situation could be the result of timing mismatches rather than information asymmetry. In order to mitigate this timing mismatch of split ratings, the thesis calculates the daily rating differences between Moody's and S&P and averages it over a fiscal year, then this split rating value is rounded to the nearest integer.[15] By doing this, any split ratings that last less than 6 months (considered as representative of timing mismatches between the two CRAs) are removed, and thus, will not enter the analysis. Timing differences based on fundamental analysis would normally be a matter of days or weeks and therefore the measures used do not suffer from any large bias.

In addition, as the thesis relies on balance sheet values, there could be a potential timing mismatch between debt maturity, leverage decisions or changes in the cost of capital and the split ratings. However, while firms' decisions on long-term debt are taken in the period prior to the observed split ratings, their decision on short-term debt, equity issues (e.g., stock repurchases) or investors' decision on firms' equity can be reflected as occurring within the period of split ratings. Additionally, split ratings are measured as average split ratings over firms' fiscal year and they represent firms' information asymmetry over the whole fiscal years. Consequently, they will inevitably be reflected in the balance sheet value. Therefore, the findings of this thesis are less likely to be affected by the timing mismatch issues than may be suggested by first impressions.

To address the superior ratings from CRAs, a second split rating variable, *SPLIT*, is calculated as the average of daily differences between Moody's and S&P (without using

[15] More details about this method are discussed in Section 3.4.4.

absolute values) to separate the effect of superior Moody's ratings and superior S&P ratings. By doing so, the positive and negative cases of the daily split can offset each other, and the direction of average rating split is preserved. This allows the test to reveal the impact of a more conservative CRAs or a more generous CRAs on the cost of equity capital. $SUP\_MOODY_{i,t}$, $SUP\_S\&P_{i,t}$, $SUP\_MOODY\_CCR_{i,t}$ and $SUP\_S\&P\_CCR_{i,t}$) are then defined according to the direction of *SPLIT* (superior Moody's ratings when *SPLIT* is positive and vice versa). Detailed definitions of these split rating variable could be found in Table 3.2.

3.4.5 Control variables

It has been shown in many previous studies that many factors other than the credit risk or default risk can affect the cost of capital. Hence, a number of other control variables are included in addition to split rating variables: systematic risk (*BETA*), financial leverage (*D2A*), growth (*BM*), earnings volatility (*STDNI*), and return on equity (*ROE*) and idiosyncratic risk (*IDIO*). *BETA* is calculated using monthly returns over the lagged 60 months; a positive coefficient on *BETA* is expected as prior studies suggested that a high level of systematic risk over time increases the return required by investors (Botosan, 1997; Gebhardt et al., 2001; Easton, 2004). BM is the ratio of book value of common equity to the market value of common equity. This definition suggests a positive sign for coefficients on BR (Gebhardt et al., 2001; Easton, 2004; Gode and Mohanram, 2003; Botosan and Plumlee, 2002). *D2A* is the ratio of total debt (*dltt* + *dlc*) to total assets (*at*). Prior studies (Botosan, 1997; Gebhardt et al., 2001; Gode and Mohanram, 2003; Easton, 2004) suggest a positive coefficient sign on financial leverage because the higher the financial leverage is the higher the risk of firms. *IDIO* is the standard deviation of the previous year's monthly returns. Prior literature suggests a positive sign for *IDIO* (Li and Mohanram, 2014) as firms with higher return volatility are more likely to have higher financing cost. *ROE* is the return on equity ratio, calculated as net income before extraordinary items and preferred dividend divided by common equity. The sign of the *ROE* coefficient is expected to be negative as firms with higher return are expected to have lower cost of capital (Hwang et al., 2013). *STDNI* is the standard deviation of quarterly net income (*ibq*) scaled by quarterly total assets (*atq*) over the last 8 quarter. The sign of *STDNI* is suggested as positive as the more volatile the firm's income is, the higher risk the firm bears (Li and Mohanram, 2014).

Furthermore, an additional set of variables is added to use with the propensity score matching that is discussed in the Section 3.4.6 bellowed. This set includes: *CASH*, the ratio of book value of cash and marketable securities (*che*) to the book value of total assets (*at*); *FS*, the nature log of total assets; *MTB*, the ratio of market value of asset to total assets; *TANG*, firm's asset tangibility; *TAXES*, the ratio of tax expenditure to book value of total assets (see Gopalan et al., 2014; Almeida et al., 2017).

All details about the control variables, including variable's description, variable's construction and data sources, could be found in Table 3.2 and Appendix 3.C.

3.4.6 Propensity score matching (PSM)

It is vital for this Chapter to address any potential endogeneity issues arising when investigating the relationship between split ratings and the cost of equity capital. Endogeneity could arise from selection bias, simultaneity and omitted variable(s) (Wooldridge, 2010). In terms of selection bias, since the main sample contains all U.S. firms rated by both Moody's and S&P, estimated results are less likely to be affected by sample selection bias. On the other hand, the regression model could suffer from the simultaneity bias or reverse causality bias, where split ratings and the cost of equity capital could be jointly determined. Current changes in a firm's cost of equity capital could lead to an adjustment in its' risk/default risk profile and consequently, might increase or decrease firm's probability of receiving split ratings in the future. Another potential problem with the regression model is the omitted variable bias, where some unobserved characteristics might have an important impact on both the dependent variable, the cost of equity capital, and the key independent variable, split ratings. In order to address these potential endogeneity issues, the propensity score matching approach is employed (e.g. Ben-Nasr et al., 2015; Khieu and Pyles, 2016; Almeida et al., 2017; Lu and Shi, 2018). The reason why PSM is used to address various endogeneity issues of the linear models is that propensity score is a nonparametric way to estimate the causal effect. PSM does not require any model functional form as well as rely on linearity assumptions outside the common support. Thus, it is less likely to suffer from the violation of parametric model assumptions (Li, 2013).

3.4.6.1 Propensity score matching

Given a sample with N units, z is the treatment condition (in this Chapter, the treatment condition is firms having split ratings from Moody's and S&P) and r is the potential response (the cost of equity capital in this Chapter). For each unit i ($i = 1, \ldots, N$), if $z_i = 1$, unit i is in the treatment group and has a potential response r_{1i}, and if $z_i = 0$ then unit i is in the control group and has a potential response r_{0i}. In order to get the causal effects, the treatment effects for each unit i are then defined as $\Delta_i = r_{1i} - r_{0i}$ (Pan and Bai, 2015). However, r_{0i} and r_{1i} cannot be observed at the same time because one unit is not able to be both treated and non-treated simultaneously. Alternatively, the Average Treatment Effect (ATE) for the population can be calculated as $ATE = E(r_1 - r_0) = E(r_1) - E(r_0)$, where $E(r_1)$ and $E(r_0)$ is the expected value of potential response in the treated group and the control group (Morgan and Winship, 2015). Unfortunately, in order to ATE to be an unbiased estimate of the treatment effect, the sample designs need to satisfy the random sampling. Apart from ATE, one might want to estimate the average treatment effect for the treated (ATT), which is estimated as $ATT = E(r_1 - r_0|z = 1) = E(r_1|z = 1) - E(r_0|z = 1)$ (Harder et al., 2010). In a normal regression method, ATT still faces the counterfactual problem that one can never observe the treated response $E(r_0|z = 1)$ of a control unit, for example, expected value of debt maturity for control group if treated is impossible to observe. Rosenbaum and Rubin (1983) propose a method called propensity score matching, which can pick a comparison group of selected treatment group and control group on the basis of estimated probability of being treated and thus, reduce the selection bias by balancing the distributions of covariates between treated and control groups.

3.4.6.2 Assumptions

In addition to a treatment condition z_i and a response r_i, each unit i has a covariate vector $\mathbf{X}_i$ of k different covariates. A propensity score then is the probability of unit i to be in the treatment group given the covariate vector $\mathbf{X}_i$, $e(\mathbf{X}_i) = \Pr(z_i = 1|\mathbf{X}_i)$ (Rosenbaum and Rubin, 1983). Thus, in order for the propensity score to be a balance score, two assumptions need to be satisfied:

$(r_{1i}, r_{0i}) \perp z_i|\mathbf{X}_i$: the conditional independence assumption. This assumption indicates that treatment z_i and response r_{1i}, r_{0i} are conditionally independent given the covariate vector $\mathbf{X}_i$. In other words, unit with similar matching characteristics ($\mathbf{X}_i$) are assigned randomly to treatment and control groups by the model.

$0 < e(\mathbf{X}_i) < 1$: the common support assumption. This assumption indicates that there is a common support between the treatment and control group, which means that units with similar characteristics ($\mathbf{X}_i$) have a positive possibility of being both treated and non-treated. The combination of the two assumptions is referred to as the “strongly ignorability” assumption (Rosenbaum and Rubin, 1983). With “strongly ignorability” assumption, the systematic, pre-treatment, and unobserved differences between treated and control units can be ruled out (Joffe and Rosenbaum, 1999). Thus, given “strongly ignorability” assumption, ATT could be unbiasedly estimated as the differences between average treatment effect of treated group and that of control group with particular propensity score.

3.4.6.3 Propensity score estimation

The propensity score of unit i, $e(\mathbf{X}_i)$, could be estimated using the logistic regression model or the probit regression model:

$$\text{Logit: } \ln\left(\frac{e(\boldsymbol{X}_i)}{1-e(\boldsymbol{X}_i)}\right) = \boldsymbol{\beta}\mathbf{X}_i$$

$$\text{Probit: } \Phi^{-1}\big(e(\boldsymbol{X}_i)\big) = \boldsymbol{\beta}\mathbf{X}_i \tag{3.9}$$

where $\Phi()$ is the cumulative standard normal distributing function, $\boldsymbol{\beta}$ is the estimated coefficients vector of $\mathbf{X}_i$. The propensity score of unit i, $e(\boldsymbol{X}_i)$, is then the probability of that unit receives the treatment/split ratings ($z_i = 1$) given its characteristic $\mathbf{X}_i$. Following previous literature (Ben-Nasr et al., 2015) this Chapter use the probit regression to calculate the propensity score.

After obtaining the propensity scores for each covariate, there are several matching methods that can be used to match units on their propensity scores, namely, nearest neighbour (NN) matching, caliper matching, radius matching, kernel matching and Mahalanobis metric matching. Each matching method has its own advantage and disadvantages with regard to reduced bias and increased variance (see Appendix 3.A for more details of matching methods). Table 3.3 presents the trade-offs of different matching methods (Baser, 2006). For example, when comparing NN matching and radius matching, the former trade-offs reduced bias with increased variance while the latter trade-offs increased bias with reduced variance.

3.4.6.4 Matching quality assessments

There are various methods to evaluate the quality of a matching. This could be both graphical or statistical evaluation. The basic idea of all matching evaluations is to compare the situation before and after matching and check if any differences remained after conditioning on the propensity score. If there are still any differences, the matching procedure is not successful. This section presents each matching evaluation method that are going to be used in this Chapter.

Selection bias

The selection bias evaluation is a two-sample t-test to test whether there are significant differences in covariate means for the treatment group and control group after matching

(Rosenbaum and Rubin, 1985a). Before matching, a significant difference between the covariate means for both groups are expected, but after matching there should be no significant differences between the covariates. However, because statistical significance testing is sensitive to sample size, they are discouraged to use for evaluating covariate balance (Imai et al., 2008).

Standardized bias

Rosenbaum and Rubin (1985a) suggest that the standardised bias (SB), which is the distance in marginal distribution of the covariates, as the indicator of matching quality. For each covariate, SB is defined as the differences between sample means in the treatment group and the matched control group. The SB before matching is estimated as:

$$SB_{Before} = 100 \times \frac{(\overline{X_1} - \overline{X_0})}{\sqrt{0.5 \times (V_1(X) + V_0(X))}} \tag{3.10}$$

The SB after matching is estimated as:

$$SB_{After} = 100 \times \frac{(\overline{X_{1M}} - \overline{X_{0M}})}{\sqrt{0.5 \times (V_{1M}(X) + V_{0M}(X))}} \tag{3.11}$$

where $X_1(V_1)$ is the mean (variance) of the covariate in the treatment group and $X_0(V_0)$ is the mean (variance) of the covariate in the control group. $X_{1M}(V_{1M})$ and $X_{0M}(V_{0M})$ are the corresponding value for the matched samples. One drawback with the SB evaluation is that there is no clear guideline of the best bias reduction for the success of the matching process. Previous literature suggests the bias reduction below 5% as a sufficient level of bias reduction (Caliendo and Kopeinig, 2008; Pan and Bai, 2015).

Joint significance and Pseudo-R^2

Another way of assessing matching quality is to re-estimate the propensity score model on the matched sample with only matched treated and non-treated unit and then compare the Pseudo-R^2 with the initial propensity score model (Sianesi, 2004; Caliendo and Kopeinig, 2008). Since there should be no systematic differences in the distribution of covariates between treated and non-treated group after matching, the pseudo- R^2 of matching sample should be fairly low compared to those of the original sample. In addition, the joint significant F-test of all covariates should not be rejected before and should be rejected after matching as there should be no systematic differences in the distribution of covariates between treated and control groups (Caliendo and Kopeinig, 2008).

3.4.6.5 Outcome analysis

Intuitively, the mean difference of the response between the treatment group and the control group in the matched sample can be used as the average treated effect on treated, ATT as $\widehat{ATT} = \overline{r_1} - \overline{r_0}$. However, because perfectly matched sample is impossible in practice, Rosenbaum and Rubin (1985a) recommend using regression with some additional unbalanced covariates to control for the chance imbalances after matching.

$$r_i = \beta_0 + \beta_1 z_1 + \gamma_k \sum_{k=1}^{q} X_{ik}^* \tag{3.12}$$

where X_{ik}^* (k = 1 … q) is the unbalanced covariate for unit i. Thus, ATT can be estimated as $\widehat{ATT} = \widehat{\beta_1}$. For NN matching, caliper matching, Mahalanobis matching, $\widehat{ATT} = \widehat{\beta_1}$ can be obtained through the Eq. (3.12) and for radius matching, kernel matching, $\widehat{ATT} = \widehat{\beta_1}$ can be obtained from a weighted regression model of Eq. (3.12). Previous literature finds that propensity score matching plus regression with controlling for unbalanced covariates produce a robust estimate of the ATT (Schafer and Kang, 2008; Shadish et al., 2008).

Nevertheless, one challenge with the propensity score matching is to choose correct covariates to estimate the propensity score. Intuitively, one would want to choose as many covariates as possible to calculate the probability of the treatment. However, in doing so, one might be in danger of picking covariates that are correlated with the treatments or covariates that are correlated with the outcomes and thus, violate the ignorability assumption. Previous literature suggests that the covariate selection should be based on theory and prior research without the observed outcomes (Rubin, 2001; Sianesi, 2004; Smith and Todd, 2005). In this Chapter, the covariates are selected based on previous credit rating literature (see Section 3.5.4)

3.5 Data and sample selection

The main sample of this Chapter contains all U.S corporations rated by both Moody's and S&P during the period from 2003 to 2017. In this section, the Compustat and Thomson Reuters Datastream databases are compared with each other in detail in order to decide which database is best suited for the purpose of this Chapter. Furthermore, this section also details the data, sample selection and variables' descriptive statistics.

3.5.1 Compustat versus Datastream database

Thomson Reuters Datastream and Compustat are two widely used databases used for empirical research in corporate finance and accounting. Thomson Reuters Datastream is a global financial and macroeconomic data platform. It has a wide range of coverage of financial market data as well as macro-economic data, such as national, financial, and external accounts. The Compustat database focuses more on corporate level data, such as financial, statistical and market information of both active and inactive firms. Furthermore, Compustat specialises in North American corporations and consequently, it is commonly used in published corporate finance research (e.g. Frank and Goyal, 2009; Kisgen and Strahan, 2010; Bedendo and Siming, 2018).

In order to consistently compare the two databases, a sample of the same companies during the same period are collected from Compustat and Datastream.[16] The final sample contains 3,850 firms and 40,988 firm-year observations across the period from 1998 to 2015.[17] The variables include earnings per share (*EPS*), book value per share (*B*), common equity (*CEQ*), common share outstanding (*CSHO*), market value (*MV*), total assets (*AT*), and total accrual (*TAC*) (Section 3.4.3 and Table 3.2 provide detailed definitions for these variables).

Table 3.4 reports descriptive statistics of all variables used to compare the two databases. In Panel A, *CEQ*, *CSHO*, *MV* and *AT* closely resemble each other across the Compustat and Datastream databases. The small differences between the two databases can be traced back to the fact that Datastream usually reports data in the calendar year while Compustat data uses the fiscal year. One disadvantage of reporting in the calendar year is that not all firms follow the calendar year when it comes to financial reporting. Indeed, the proportion of firms not following the calendar year in our initial sample and final sample are 23.4% and 23.6%, respectively. Another drawback of using calendar year reporting is that when firms change their time of reporting the data, there might be a gap in the database if reported in the calendar year.[18] Thus, the common practice in financial research and literature is to use the fiscal year data (see, for example, Rauh and Sufi, 2010; Li and Mohanram, 2014; Bedendo and Siming, 2018; Brooks et al., 2018). The small differences among those variables

[16] Because the two databases use different identification for firms, Ticker are used to match firms between two databases.
[17] The shorter period used in this sample in comparison with the one used in the RI model is due to the availability of firms' ticker data. Furthermore, even though the main sample period is up to 2017 (See Section 3.5.2), this investigation is still valid when comparing the two databases.
[18] In our initial sample, 96 firms change the month of reporting during the period. For example, Novelis Inc changed it from December in 2006 to March in 2007.

in Table 3.4 are also consistent across different periods as can be seen in Panel B, C, and D. The larger differences between Datastream's *B* and Compustat's *B* are due to the small differences of *CEQ* and *CSHO* because *B* is calculated by dividing common equity by common share outstanding.

Compustat's *EPS* variable is significantly and systematically lower than Datastream's *EPS*. This difference is due to both the differences in annual data types (calendar vs. fiscal) and in the formula used to calculate *EPS*. Datastream's *EPS* uses income before extraordinary items while Compustat's *EPS* uses income before extraordinary items and special items (as Datastream do not have the special items datatype).

Datastream has limited data in one of the *TAC* components, for example, short-term investment, and since missing *TAC* is set 0, Datastream's *TAC* is significantly lower than the Compustat counterpart for the whole sample as well as across different sub-sample periods.

Although the difference between the two databases is modest, Compustat is used in this Chapter because of the greater availability of accounting data (especially regarding short-term investment and special items). Another reason for choosing Compustat is the advantage of the fiscal year account reporting as well as prominent examples from the closely related literature use Compustat (Li and Mohanram, 2014; Abdoh and Varela, 2017; Badoer and Demiroglu, 2018; Bedendo and Siming, 2018;)

3.5.2 Data and sample selection for the dependent variable

In order to calculate the implied cost of capital for the main regression, historical accounting data of all U.S. listed firms are collected from the Compustat database.[19] Information on stock price, net income before extraordinary items, book values, dividends, shares outstanding should be non-missing for firm-year observation. Firms can enter and exits freely from the sample to reduce the impact of survival bias. Each firm-yesar observation should have information on accounting data such as: total assets, current assets, current liabilities, cash and short-term investments. Each variable in the data set is the fiscal year data.

[19] Following Li and Mohanram (2014), financial firms (SIC code from 6000 to 6999) are excluded from the sample. This is also a common practice in credit ratings and cost of capital literature (see, for example, Kisgen, 2006; 2009; Almeida et al., 2017).

To generate earnings forecasts for calculating the implied cost of equity capital, a sample of all listed U.S. firms from 1986 to 2017 are used.[20] The sample selection procedure for all U.S. firms is shown in Table 3.5. After removing any missing accounting data, namely, earnings per share (*EPS*) and book value per share (*B*), the sample is winsorized at the 1st and 99th percentile to remove any potential outlier (Li and Mohanram, 2014). The final sample for the cross-sectional regression model is 219,349 firm-years and 23,282 unique firms. The large number of observations allows the result for the earnings forecast to be more representative. The descriptive statistics of the sample are shown in Table 3.6. The mean of *B*, *EPS*, and *TAC* are 179.8, 5.636, and 0.356, respectively.

The sample data are then used as the input for the cross-sectional model to generate coefficients for forecasting future earnings. The forecasting period is from 2003 to 2017. Each year, 5 pooled cross-sectional models representing 1- 2- 3- 4- and 5-year ahead forecasts earnings are estimated using data from the previous 10 years. As a result, each year from 2003 to 2017 will have 5 regression models to generate 1-,2-, …, 5-year ahead earnings forecasts for that given year.

Table 3.7 presents the statistical descriptions of the average coefficients estimated from the cross-sectional RI model. The signs of all coefficients are consistent with prior expectations. The positive sign of *B* and *E* implies the persistence of losses, while the negative coefficient on *NE* implies the low persistence of losses. Moreover, the negative sign of *TAC* coefficient shows the effect of conservatism, which mean higher capital expenditures (accruals) will depress future residual income (Feltham and Ohlson, 1995; Li and Mohanram, 2014).

The coefficients calculated from the cross-sectional model, Eq. (3.4), (see Section 3.4.3.1) are then used as the input to produce the earnings forecasts for rated firms. The procedure is to use the firms' specific characteristics (earnings, book value and total accruals) and multiply them with the corresponding coefficients each year. The summary statistics of the results of this process are shown in Table 3.8.[21] On average, firms in the sample have positive forecasted earnings per share. *EPS* during the period of the financial crisis, 2007 – 2009, are slightly lower than the pre- and post-crisis period, suggesting that the model results are able to reflect the economic events.

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[20] The reason for starting with 1986 is that data from year $t - 1$ to $t - 15$ is required to calculate earnings forecasts for year t.

[21] This table shows statistical description of the cost of equity capital for rated firms before removing missing observations, and winsorizing.

The summary results of the four ICC model and the average of the four measures are shown in Table 3.9. The average ICC calculated by using the RI model is 7.34%, which is slightly lower than that of Gupta (2018) 8.52%, and Li and Mohanram (2014) 9.2%, respectively. This could be due to the selected sample for this research contains only rated firms from 2003 to 2017 while that of Gupta (2018) is an international corporate sample from 2002 to 2012 and Li and Mohanram (2014) is all U.S. corporate sample from 1969 to 2012. Panel B of Table 3.9 presents the correlation matric for ICC estimates. The internal validity of ICC estimates is confirmed due to the fact that all the ICC estimates are significantly and positively correlated with each other.[22]

Table 3.10 shows the descriptive statistics for all ICC estimates for three different periods. As expected, the ICC of rated U.S. firms is the highest during the crisis period 2007-2009 for all models, reaching 9.41% on average. During the financial boom period (before the crisis) the average ICC is the lowest, at only 6.20%. The effect of the crisis on firms has not yet worn off as the average ICC of the post-crisis period is 6.97%, higher than that of the financial boom period. In summary, the ICC measures are able to capture the effect of macroeconomic events, such as the U.S. subprime mortgage crisis.

Tables 3.11 and 3.12 show the descriptive statistics of ICC estimates for the main sample (the regression sample). The relationship among ICC measures and COEC for different periods are still intact and are similar to those in the initial sample. All ICC measures and the average ICC are still highly and significantly correlated with each other. However, the mean of ICC measures and average ICC are slightly smaller in the main sample than in the initial sample. This is because observations with large ICC are removed as the result of winsorizing.

3.5.3 Split ratings

Split ratings are defined as the fiscal year-end average of the absolute daily difference in ratings between the two CRAs. More detail about the definition of split ratings can be found in Section 3.4.4.

Table 3.13 reports the data summary for both absolute annual split ratings and split ratings. As can be seen from the samples, split ratings are very common. The proportion of absolute split ratings over the whole sample is 68.0% while the proportion of split ratings is

[22] ICCOL and ICCGLS are less correlated compare to other pair of ICC. This may be due to that GLS is the most sophisticated method and requires the longest horizon among those four methods.

65.6%. Most of the disagreements are below 3 CCR units, made up about 52.5% of the whole sample. Absolute split ratings above 3 CCR units account only for 15.5%, showing that large splits are uncommon. Panel B describes the split ratings in total and in two different cases, when S&P ratings are superior to Moody's and the other way around. As can be seen, split ratings with superior Moody's ratings make up only about 19% of the whole sample while split ratings with superior S&P ratings are about 45.8%, more than twice the frequency of superior Moody's split ratings. This suggests that Moody's is a more conservative CRA compared to S&P. In other words, S&P is a more generous CRA than Moody's. This is consistent with the finding of Livingston et al. (2010).

Table 3.14 shows the statistical properties of split ratings during three different sub-periods: pre-crisis, crisis, and post-crisis. For both absolute split ratings and split ratings, the proportion of split ratings reduce during and after the crisis. Before the crisis, split ratings are about three-quarters of the total, however, after the crisis, the proportion of split ratings drops to about two-thirds of the total number of observations. This is related to the counter-cycle property of CRAs, meaning CRAs' ratings tend to be inflated during the financial boom and become more accurate during the financial crisis period (Bar-Isaac and Shapiro, 2013). This is also consistent with the finding of Baghai et al. (2014), which suggest that CRAs have become more conservative over time. From Table 3.14, Moody's and S&P disagreements are lower after the U.S. subprime mortgage crisis.

3.5.4 Control variables

To control for differences in firms' characteristics, number of variables consist of *ROE*, *D2A*, *BM*, *BETA*, *STDNI*, and *IDIO* are used. More details about the definition and construction of these variables could be found in Table 3.2. The descriptive statistics and pairwise correlation of all variables are presented in Table 3.15. The mean value of *D2A* is about 31.9%, suggesting that firms in the sample rely more on equity financing than debt financing. The correlations among control variables are examined in Panel B and significant at 1%. There is no serious collinearity among control variables. Split rating measure (*ASPLIT*) is negatively correlated with *ROE* and positively correlated with *D2A*, *IDIO* and *BM*. This suggests that firms with high split ratings are less profitable, higher leverage, higher return volatility and fewer growth opportunities. In addition, another set of covariates, including idiosyncratic risk (*IDIO*), firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*) and taxes over total assets ratio (*TAXES*) (more details appear in Table 3.2), are used to generate the propensity scores for the PSM. They are chosen base on previous credit rating literature (Gopalan et al., 2014; Almeida et al., 2017).

3.6 Empirical results

3.6.1 Baseline model

This section discusses the results of Eq (3.1), which investigates the cost of equity capital for split rated corporations (Hypothesis 1). The dependent variable is the cost of equity capital, calculated as the average of four ICC measures, in percentage. The explanatory variables include split ratings and control variables. The key variable is absolute split ratings, ASPLIT, which is the average of absolute daily rating differences over the fiscal year. If equity investors require a higher risk premium for split rated firms, the coefficients on ASPLIT should be significantly positive.

Table 3.16 reports the regression results of Eq (3.1). The coefficients on *ASPLIT* is 0.138 and significant, suggesting that on average the cost of equity capital for one CCR unit (one-notch) split rated firms is about 14 (42) basis point higher than the cost of equity capital for non-split rated firms with similar credit risk. These results confirm the alternative Hypothesis 1 that split ratings signal uncertainty about firms' creditworthiness and investors require a premium to compensate for this ambiguity. The results are in line with the findings of Livingston and Zhou (2010) and Livingston et al. (2010) that bond investors require a higher premium for split rated bonds than non-split rated bonds of similar credit risk. Livingston and Zhou (2010) and Livingston et al. (2010) argue that split ratings are also a sign of firms' information opaqueness problem. Information opacity is a sign of information asymmetry problem between firms and investors (Ravi and Hong, 2014). Thus, it leads to a higher adverse selection problem and consequently increases the cost of equity capital of split-rated firms. The results also suggest that equity investors and bond investors have similar reactions when it comes to CRAs disagreement about firms' credit ratings. However, equity investors tend to act more drastically than bond investors as they require higher premium when split ratings occur than bond investors. The possible reason for this is due to the nature of equity investments that are much riskier than debt investments in general because equity investors are part owners of firms while bond investors are creditors of firms. Hence, equity investors bear more risk than bond investors and indeed require a higher risk premium than bond investors.

Column (II) of Table 3.16 reports the regression results of Eq (3.1) using a split rating dummy variable, *ASPLIT_DUMMY*, which is equal to 1 if *ASPLIT* is positive and 0 otherwise. The coefficient on *ASPLIT_DUMMY* is 0.539, positive and significant at 5% level, suggesting that on average firms with split ratings have about 54 basis point higher cost of equity capital compare to a non-split rated firm. This result is consistent with the baseline model.

The coefficients of the control variables have the expected sign if significant. Return on equity (*ROE*) has a negative effect on the cost of equity capital. Firms with high return have lesser risk and consequently a lower cost of equity than firms with low or negative return. Two other risk factors, leverage (*D2A*) and earnings volatility (*STDNI*) have a positive impact on the cost of equity capital. Firms with high leverage and large earnings volatility are more likely to have a higher risk and thus, higher cost of equity capital than their other peers.

3.6.2 Cross-sectional tests

A number of cross-sectional tests are conducted to further investigate the relationship between the cost of equity capital and split ratings. Whether the relationship between split ratings and the cost of equity capital varies across different sized firms, for speculative versus investment-grade companies and through different economic conditions are examined. Following Gopalan et al. (2014), six dummies are created and interacted with *ASPLIT* in Eq. (3.1). The dummy variables are *SMALL*, (1-*SMALL*), *INVST*, (1-*INVST*), *CRISIS* and (1-*CRISIS*). *SMALL* is a dummy variable equal to 1 if a firm has a below-sample-median value of *FS* in year t – 1 and 0 otherwise. *INVST* is a dummy variable equal to 1 if a firm has an investment-grade rating (Baa3/BBB- or above) in year t – 1 and 0 otherwise. *CRISIS* is a dummy variable equal to 1 during the U.S. sub-prime crisis period (2007 – 2009) and 0 otherwise.

Table 3.17 reports the results of Eq. (3.1) with the aforementioned three sets of interaction terms. Column (I) of Table 3.17 presents the regression results of two interaction terms, *ASPLIT*×*SMALL* and *ASPLIT*×(1-*SMALL*). The coefficients of *ASPLIT*×*SMALL* are positive and significant at the 1% level while those of *ASPLIT*×(1-*SMALL*) are insignificant, suggesting that the positive effect of split rating on the cost of equity capital is predominantly associated with small firms. Large and more diversified firms tend to have lower default risk compare to small firms (Frank and Goyal, 2009). Since small firms are generally riskier than large firms, they are more sensitive to any negativity towards firms' creditworthiness. Thus, they are more likely to suffer from the uncertainty about their credibility bringing about by split ratings. In addition, the comparison of two interaction terms' coefficients shows that the two coefficients are significantly different from each other (see the row titled ΔCOEF).

Column (II) of Table 3.17 reports the results of Eq. (3.1) with two interaction terms *ASPLIT*×*INVST* and *ASPLIT*×(1-*INVST*). The coefficients on *ASPLIT*×(1-*INVST*) are positive and significant, suggesting that the higher cost of equity capital is predominantly associated with a split rating for firms with speculative-grade ratings. Possessing a credit rating is an information revelation process through CRAs. Thus, firms with higher ratings are less likely to suffer from an adverse selection problem and vice versa (Frank and Goyal, 2009). Because split ratings are a sign of information opaqueness or information asymmetry between firms and investors, receiving different opinions from CRAs could further exacerbate the current adverse selection problem of speculative-grade firms. This consequently increases these firms' cost of equity capital. The two coefficients of the two interaction terms are not significantly different from each other (see the row titled ΔCOEF).

Column (III) of Table 3.17 reports the results of Eq. (3.1) with two interaction terms, *ASPLIT*×*CRISIS* and *ASPLIT*×(1-*CRISIS*). The results show that the coefficient of *ASPLIT*×*CRISIS* is positive and highly significant while those of *ASPLIT*×(1-*CRISIS*) are positive but insignificant. This implies that the significant effect of split ratings on the cost of equity capital is stronger during the crisis period. During the sub-prime mortgage crisis, when the equity market is in a bust cycle, any negative news about a firm's creditworthiness could lead to an adverse action towards that firm. Hence, split ratings as an indication of uncertainty are more likely to increase firms' cost of equity capital during the crisis period. The coefficients of two interaction terms are not significantly different from each other (see the row titled ΔCOEF).

3.6.3 Results of the investigation of endogeneity

One concern regarding the research design of this Chapter is that the baseline results could potentially suffer from endogeneity issues. Such issues could exist in the form of sample selection bias, simultaneity/reverse causality, where the cost of equity and split ratings are jointly defined. Alternatively, there may be omitted variable bias, where unobserved variables are correlated with both the cost of equity capital and split ratings. In order to address these key issues, the propensity score matching is employed with three different matching approaches, NN matching, radius matching and kernel matching.[23] In this Chapter, the treated group is set as firms which receive split ratings from Moody's and S&P and the control group is set as firms which receive the same ratings from Moody's and S&P. The covariates used to generate the propensity scores are idiosyncratic risk (*IDIO*), firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*) and taxes over total assets ratio (*TAXES*).

3.6.3.1 Nearest neighbour matching

NN matching is one of the basic and easy to implement matching techniques (Rubin, 1973). In NN neighbour matching, a unit from control groups is matched with a treated unit when the absolute distance between the two units' propensity score is minimum. NN matching has two variants, "with replacement" and "without replacement". Since the main sample number of treated/split-rated units (4,221 observations) are much larger than the number of control/non-split units (2,037 observations), the NN matching "with replacement" is employed so one control unit could be matched with multiple treated units. In addition, a caliper band of 0.01 is applied so that the smallest distance between treated and control unit's propensity score is limited to 1%. By doing so, the quality of matching is improved as bad matches are left out of the sample.

Table 3.18 reports all matching quality investigations. Panel A of Table 3.18 shows that most of the covariates have significantly reduced standardised bias after matching, especially for high bias covariates like *IDIO* and *FS*. The t-test results of all covariates, which are all rejected after matching, indicate the distribution of covariates between treated groups and control groups in the matched sample are indeed similar to each other. Panel B and Panel C of Table 3.18 shows the ATT, joint significant and R-squared test for the NN matching. Overall, all the quality tests confirm that the NN matching with replacement and caliper of 0.01 is sufficient in producing a matched sample.

Table 3.19 presents the propensity score regression results for PSM (Column (I)) and the main regression results using Eq. (3.1) with the matched sample generated from PSM (Column (II) and (III)). The coefficient of *IDIO* is positive and significant at the 5% level, suggesting firms with high idiosyncrasy risk are more likely to be split rated. The coefficient on *TAXES*, *FS* and *TANG* are positive and significant at the 5% level, indicating that firms with high level of taxes expenses, book value of assets or assets tangibility are less likely to be split rated. The result of Eq. (3.1) reported in Column (II) and (III) are consistent with the baseline

[23] More details about these methods could be found in Appendix 3.A.

model (see Section 3.6.1), where both coefficients of *ASPLIT* and *ASPLIT_DUMMY* are positive and highly significant. Thus, this suggests that the baseline results are robust and the baseline model is less likely to suffer from the endogeneity problems.

3.6.3.2 Other matching methods

In addition to NN matching, two other matching methods, radius matching and kernel matching, are employed to further address the concern of endogeneity. The quality investigation results and regression results of the two methods are reported in Appendix 3.B, Table 3.B.1, Table 3.B.2, Table 3.B.3 and Table 3.B.4. Overall, the results from both radius matching and kernel matching are consistent with those of NN matching as well as of baseline model, indicating that the main research design is less likely to be affected by endogeneity issues.[24]

3.6.4 Additional robustness test

Livingston and Zhou (2010) suggest a method which is able to differentiate between the information risk and credit risk elements of split ratings. The methodology is to compare the actual level of bond yield with the estimated bond yield if both CRAs had assigned the same inferior/superior ratings. Thus, the difference between the average of the two estimated bond yields and the actual bond yield of split rated bond contributes to identify the information risk element of split ratings.

In this thesis, the rounded average rating from Moody's and S&P (in rating levels) is used when defining split ratings for the empirical analysis. Thus, the thesis faces a potential issue in cases when the average ratings are exactly in the middle of a one-notch split between Moody's and S&P ratings (e.g., a BBB+/BBB split). In this case, the main reported models might not be able to separate the effect of the information risk of split ratings from the effect of the credit risk element of split ratings. Thus, in order to deal with this potential problem, the thesis employs the method developed by Livingston and Zhou (2010) as a robustness test (see Appendix 3.D for more details).

Table 3.D.1 reports the results of this estimation using Livingston and Zhou's (2010) method. The cost of equity capital for split rated firms is 43.7 basis points higher than the

[24] In addition to PSM, an additional robustness is added to address the issue of setting the total accruals (*TAC*) to 0 when missing because this could lead to potential bias of the main results. Eq. (3.1) is then re-estimated with a new *COEC* generated from the RI model that drops all observations that missing *TAC*. Table 3.B.5 of Appendix 3.B reports the results of re-estimating Eq. (3.1) with this new *COEC* and the results are still robust.

estimated cost of equity capital for these firms if both CRAs had assigned the same inferior ratings. The results suggest that the impact of split ratings on the cost of equity capital is indeed caused by information risk (information asymmetry). The results of this robustness test are consistent with the baseline results (see Table 3.21) yet are helpful in reinforcing the main inferences for the chapter.

3.7 Superior Moody's rating versus superior S&P rating and the cost of equity capital

The previous section examines the impact of split ratings on the cost of equity capital without considering the direction of the split. However, previous literature (Livingston et al., 2010) shows that ratings from Moody's and S&P are not equivalent to each other when it comes to split opinions. Thus, one might expect that split ratings with superior Moody's ratings have a different impact on the cost of equity capital compared to those with superior S&P ratings. To address this issue, Eq. (3.2) and Eq. (3.3) are estimated with two sets of variables, *SUP_MOODY* (*SUP_S&P*), and *SUP_MOODY_CCR* (*SUP_S&P_CCR*).

Table 3.20 shows the results of Eq. (3.2) and Eq. (3.3). The coefficients for *SUP_MOODY* and *SUP_MOODY_CCR* are positive and highly significant, while those for *SUP_S&P* and *SUP_S&P_CCR* are insignificant. The positive relationship between split with superior Moody's ratings and the cost of equity capital suggests that firms with superior Moody's ratings tend to have a higher cost of equity than non-split rated firms and firms with superior S&P ratings. The coefficient on *SUP_MOODY_CCR* is 0.174, indicating that one notch split rated firms with superior Moody's ratings have about 52 basis points higher in the cost of equity capital than non-split rated firms or firms with superior S&P ratings.

The results are in contrast with Livingston et al.'s (2010) findings. They reports that firms with superior Moody's ratings have significantly lower bond yields than firms with superior S&P ratings. The reason for this contradiction arises from the different nature of bond and equity investors. Where bond investors are the creditors of firms; equity investors are considered to be partial owners (shareholders) of those firms. Accordingly, equity investors tend to require higher returns as investing in the equity market is riskier than in the capital market. Thus, one might expect bond investors and equity investors to react differently given the news regarding firms' default risk. Indeed, earlier studies have shown that bond investors and firms have different attitudes towards Moody's and S&P ratings. Issuers consider S&P

ratings as more accurate than Moody's ratings; while investors put more weight on Moody's ratings than S&P ratings (see Baker and Mansi, 2002).

The cost of equity capital for firms with superior Moody's ratings are significantly higher than for firms with superior S&P ratings or non-split rated firms, suggesting that equity investors assign more weight to S&P ratings (even when S&P is the more generous CRA as they assign more favourable ratings than Moody's) when assessing the cost of equity capital. Alsakka and ap Gwilym (2012b) find that Moody's concern more about stability while S&P emphasizes on short-term accuracy. In addition, in a survey of 200 plan sponsors and investment managers, Cantor et al. (2007) find that rating accuracy is more important to plan sponsors and investment managers than rating stability. This helps to explain the reason why equity investors are putting more weight on S&P ratings than Moody's ratings as they concern more about rating accuracy than rating stability. This finding reveals an interesting relationship between equity investors and credit ratings. The results are in-line with Baker and Mansi's (2002) findings that issuers prefer S&P ratings while bond investors prefer Moody's ratings.

To sum up, S&P emphasizes timely rating while Moody's focuses more on rating stability. As a result, equity investors place more weight on S&P ratings than Moody's when assessing the cost of equity capital. This finding suggests that equity investors rely more on CRAs emphasizing timely ratings than CRAs emphasizing rating stability.

3.8 Conclusion

Although most U.S. bond issues and issuers receive ratings from the two major CRAs, Moody's and S&P, academic studies and financial regulators typically do not consider them differently and normally treat them as equal and interchangeable. This suggests that split rated firms from the two CRAs are treated the same as non-split rated firms with similar credit risk. This Chapter investigates whether (i) equity investors recognize the ambiguity of CRAs disagreement upon firms' creditworthiness and (ii) equity investors differentiate between superior Moody's and superior S&P ratings. In the sample, firms have an average cost of equity capital of 6.6%. However, during the crisis period (2007 – 2009), firms' cost of equity capital rose to about 8% i.e. suggesting that firms face higher financing cost during a period of economic downturn. CRAs' disagreement upon firms' creditworthiness is common within the data sample, as two-thirds of observations are split rated. In addition, the sample contains more than twice as many superior S&P ratings versus superior Moody's ratings, suggesting that S&P is indeed a more generous CRA than Moody's. This is consistent with the finding of Livingston et al. (2010) regarding bond issues' ratings.

This Chapter hypothesizes that disagreement between CRAs about firms' creditworthiness could have a significant impact on firms' cost of equity capital. Split ratings could signal uncertainty about firms' creditworthiness as well as indicating firms having an information opaqueness problem. Because information opacity indicates information asymmetry between firms and investors, firms with split ratings would consequently have higher information asymmetry problem than non-split rated firms. Because a greater information asymmetry/adverse selection problem leads to a higher financing cost of capital (Botosan and Plumlee, 2002; Hughes et al., 2007), split rated firms are expected to have a higher cost of equity capital compared to their non-split rated peers.

Table 3.21 provides a brief summary of this Chapter's empirical findings. This Chapter reveals that split rated firms indeed have a higher cost of equity capital than non-split rated firms with similar credit risk, suggesting that equity investors differentiate between the split rated and non-split rated firms. The premium that investors charge in the case of split rated firms is about 42 basis points for a one-notch rating split (3 CCR units). The magnitude of this premium is larger than that reported in the literature for investors in the bond market, suggesting that equity investors are at least equally concerned about firms' credit risk and place more weight on default risk while assessing the cost of equity capital. The main results are more prominent for small firms and those with speculative-grade ratings. Small firms and speculative-grade firms are more sensitive towards any negativity surrounding their creditworthiness. Split ratings could exacerbate any prevailing adverse selection problem of these firms and consequently affect their cost of equity capital. In addition, the impact of split ratings on the cost of equity capital is stronger during the sub-prime crisis period.

This Chapter offers empirical evidence on whether equity investors consider split ratings as new information about firms' creditworthiness. Existing studies show that information opacity is one of the reasons that split ratings occur (see, e.g., Morgan, 2002; Livingston and Zhou, 2010) and information opacity signals the information asymmetry problem between firms and investors (Ravi and Hong, 2014). The results suggest that equity investors recognize these problems of split rated firms and adapt their expectations accordingly. Thus, the finding offers strong support to the empirical results of Livingston et al. (2010) that split ratings bring new information about firms' credit risk to the markets. The findings also suggest that both bond investors and equity investors have similar actions towards split rated firms and charge these firms higher premia compared with non-split rated firms. However, due to the nature of equity investments (riskier than bond investments), equity investors react more drastically and demand greater premium (in terms of magnitude) than bond investors when split ratings emerge.

The results also reveal that equity investors differentiate between split rated firms with superior Moody's ratings and split rated firms with superior S&P ratings. Split rated firms with superior Moody's ratings have a significantly higher cost of equity capital than split rated firms with superior S&P ratings. This evidence indicates that equity investors place more weight on S&P ratings, the more generous CRA, than Moody's when assessing the cost of equity capital. The results contrast with evidence from the bond markets where it appears that bond investors assign more weight to Moody's ratings. This could be the result of the differences between bond investors (firms' debtors) and equity investors (firms' owners). Indeed, the results are consistent with Baker and Mansi's (2002) survey findings that issuers prefer S&P ratings while investors prefer Moody's ratings.

This Chapter employs the propensity score matching method to rule out potential endogeneity issues, including sample selection bias, simultaneity/reverse causality bias or omitted variable bias. Together with PSM, various matching methods, including NN matching, radius matching and kernel matching, are implemented. The results from PSM are consistent with the main baseline model, suggesting that the inferences from the baseline model are unlikely to suffer from an endogeneity issue.

This Chapter offers a novel contribution to the existing credit ratings and cost of capital literature. It shows that both major CRAs are important for equity investors, firms and real economic outcomes. The findings suggest that both ratings from Moody's and S&P contribute additional information to the market. The main inference from the findings is that split ratings have a significant economic impact on firms and both equity and bond investors recognize that there are systematic differences across CRAs. One implication of the findings is that firms should grasp any opportunities to reduce the likelihood of CRAs' disagreement and thereby lower their cost of equity capital by reducing information opacity. Extensive existing literature already documents that firms' cost of debt can be significantly reduced by employing high-quality accounting standards, an important mechanism for tackling information opacity (Sengupta, 1998; Yu, 2005). Hence, firms can also reduce the cost of equity capital by the pursuit of the same policy. The findings also strengthen the argument for the need for regulatory agencies, for example, the Securities and Exchange Commission (SEC), to monitor and evaluate the performance of NRSROs.

Table 3.1. Four different ICC approaches to calculate COEC

ICC approaches	ICC model	Formula	Source
Residual income model (RIM)	GLS	$$P_0 = B_0 + \sum_{t=1}^{12} \frac{E_t - R_E^{GLS} \times B_{t-1}}{(1 + R_E^{GLS})^t} + + \frac{(E_{12} - R_E^{GLS} \times B_{11})}{(1 + R_E^{GLS})^{12} R_E^{GLS}}$$ where $P_0$is the firm current price, B_t is the book value per shares at time *t*, E_t is the earning at time *t*, the forecasts earnings per share from *t + 1* to *t + 5* are obtained from the model and then applying ROE convergence. $E_t - R_E^{GLS} \cdot B_{t-1}$ is the residual income at time *t*	Gebhardt et al (2001)
	CT	$$P_0 = B_0 + \sum_{t=1}^{5} \frac{E_t - R_E^{CT} \times B_{t-1}}{(1 + R_E^{CT})^t} + \frac{(E_5 - R_E^{CT} \times B_4)(1 + g)}{(1 + R_E^{CT})^5 (R_E^{CT} - g)}$$ $P_0$is the firm current price, B_t is the book value per shares at time *t*, E_t is defined similarly to the GLS model above. $E_t - R_E^{CT} \cdot B_{t-1}$ is the residual income at time *t*, R_E^{CT} is the cost of equity capital and g is the long-term growth rate and is set as r_f – 3% where r_f is the risk-free rate (U.S. 10-year Treasury bonds yield).	Claus and Thomas (2001)
The abnormal earnings growth model (AEGM)	OJ	$$R_E^{OJ} = A + \sqrt{A^2 + \frac{E_1}{P_0}(g_2 - (\gamma - 1))}$$ where $$A = \frac{1}{2}((\gamma - 1) + \frac{D_1}{P_0})$$ $$g_2 = \frac{E_2 - E_1}{E_1}$$ R_E^{OJ} is the firm cost of equity capital, E_1 is the earnings at time *1*, $P_0$is the firm current price, $(\gamma - 1)$ is set to be r_f – 3%. g_2 is set to be the geometric mean of short-term growth $(\frac{E_2 - E_1}{E_1})$ and long-term growth rate $(\sqrt[4]{\frac{E_5}{E_1}} - 1)$ if long term growth rate is less than short term growth rate. Otherwise, $g_2$is set as long-term growth rate. Dividends are calculated as dividends divided income before extraordinary items if earnings are positive and as dividends divided by 6% total assets if income before extraordinary items is negative.	Ohlson and Juettner-Nautoth (2005)
	PEG	$$R_E^{PEG} = \sqrt{\frac{E_2 - E_1}{P_0}}$$	Easton (2004)

Table 3.2. Variable definitions

Variable	Definition	Construction	Data Sources
COEC	COEC is the implied cost of equity capital calculated by using the RI model and 4 different commonly used metrics, GM, PEG, GLS and CT.	COEC is calculated as the average of the four estimated ICC: GM, PEG, GLS and CT.	Compustat
ASPLIT	Absolute split ratings are the rounded average of absolute daily differences between Moody's and S&P over a calendar year. More than 4-CCR unit ASPLIT is set to be 4.	|Moody's rating – S&P rating|	Moody's website and Capital IQ
SPLIT	Split ratings are the average of daily differences between Moody's and S&P over a calendar year.	(Moody's rating – S&P rating)	Moody's website and Capital IQ
ASPLIT_DUMMY	ASPLIT_DUMMY is a dummy variable, taking the value of 1 if ASPLIT is positive and, 0 otherwise.	ASPLIT_DUMMY = 1 if ASPLIT > 0 ASPLIT_DUMMY = 0 if ASPLIT = 0	Moody's website and Capital IQ
SUP_MOODY (SUP_S&P)	SUP_MOODY (SUP_S&P) is a dummy variable, taking the value of 1 if SPLIT is positive (negative) and, 0 otherwise.	SUP_MOODY (SUP_S&P) = 1 if SPLIT > 0 (< 0) SUP_MOODY (SUP_S&P) = 0 if SPLIT <=0 (>= 0)	Moody's website and Capital IQ
SUP_MOODY_CCR (SUP_S&P_CCR)	SUP_MOODY_CCR (SUP_S&P_CCR) is a variable taking the value of SPLIT if SPLIT is positive (negative) and, 0 otherwise.	SUP_MOODY_CCR (SUP_S&P_CCR) = SPLIT if SPLIT > 0 (< 0) SUP_MOODY_CCR (SUP_S&P_CCR) = 0 if SPLIT <=0 (>= 0)	Moody's website and Capital IQ
BETA	Firm systematic risk	BETA is calculated using monthly returns over the lagged 5 years.[25]	Compustat
BM	The ratio of book value of common equity to market value of common equity (Duqi et al., 2015)	$\frac{bvps}{prcc\_f}$	Compustat
D2A	The ratio of total debt to total assets.	$\frac{dlc + dltt}{at}$	Compustat
IDIO	The standard deviation of the prior year's monthly returns.	The standard deviation of firms' past year's monthly returns (TRT1M).[26]	Compustat

[25] BETA could be obtained from Compustat database by creating two custom concepts: total monthly return; TRT1M = (((*prccm***trfm*)/(*prccm***trfm*)[-1])-1)*100; and BETA = (@PCOR(TRT1M,"I0003":TRT1M,-59,0)*@PSTD(TRT1M,-59,0))/(@PSTD("I0003":TRT1M,-59,0)).

[26] IDIO could be obtained from Compustat database by creating a concept: IDIO = @PSTD(TRT1M,-12,0).

Table 3.2. Continued.

Variable	Definition	Construction	Data Sources
ROE	ROE is the return on equity calculated as net income before extraordinary items and preferred dividend divided by common equity.	$\frac{ib}{ceq}$	Compustat
STDNI	The standard deviation of net income scaled by total assets measured over the previous 8 quarters.	The standard deviation of ibq/atq for the last 8 quarters	Compustat
CASH	The ratio of book value of cash and marketable securities to the book value of total assets.	$\frac{che}{at}$	Compustat
FS	Firm size is the natural log of total assets (Mouselli et al., 2013; Ben-Nasr et al., 2015; Díaz-Díaz et al., 2016; Huang et al., 2016).	$ln(at)$	Compustat
MTB	Market to book ratio is the ratio of market value of asset to total assets (González, 2015; Ben-Nasr et al., 2015; Huang et al., 2016).	$\frac{MVA}{at}$ [27]	Compustat
TANG	Firms' assets tangibility (Lemmon et al., 2008; Kirch and Terra, 2012).	$\frac{ppent}{at}$	Compustat
TAXES	The ratio of tax expenditure to book value of total assets.	$\frac{txt}{at}$	Compustat
LEVEL	Set of 19 dummy variables represent the rating categories of a firm calculated as the rounded average of annual average of Moody's and S&P daily ratings	Rounded value of ([Moody_Rating + S&P_Rating]/2)	Moody's website and Capital IQ
YEAR*INDUSTRY	Interactions between two dummy groups, YEAR and INDUSTRY, to control for the macro-economic changes.	YEAR: a set of dummy variables equal to 1 for the given year and 0, otherwise. INDUSTRY: a set of dummy variables for 1-digit SIC industries.[28]	Compustat

Note: Table 3.2 provides the definitions of all used variables and data sources.

[27] *MVA = dlc + dltt + pstkl + csho*prcc_f – txditc*. Details of Compustat items can be found in the Appendix 3.C

[28] 1-digit SIC industry dummies are used to persevere the degree of freedom as the interactions between YEAR and INDUSTRY increase the number of variables used exponentially. However, robustness tests estimating Eq. (3.1), Eq. (3.2) and Eq. (3.3) with 2-digit SIC industry dummies produce similar results.

Table 3.3. Trade-offs in terms of bias and efficiency

Matching methods	Bias	Variance
Nearest neighbour (NN) matching		
Multiple neighbours / single neighbour	(+)/(–)	(–)/(+)
With / without caliper	(–)/(+)	(+)/(–)
Mahalanobis metric matching		
With / without caliper	(–)/(+)	(+)/(–)
Bandwidth choice of kernel matching		
Small/large	(–)/(+)	(+)/(–)
NN matching/ Radius matching	(–)/(+)	(+)/(–)
Kernel or Mahalanobis matching/ NN matching	(+)/(–)	(–)/(+)

Note: Table 3.3 presents trade-offs in terms of bias and variance across different matching methods including nearest neighbour matching, caliper matching, radius matching, kernel matching and Mahalanobis matching. For example, with NN matching with caliper, the quality of matching increases and thus, the bias decreases but the variance increases because of the use of less information to contruct the counterfactural. (+), increase; (–), decrease.

Table 3.4. Summary statistics of accounting data - Compustat versus Datastream

Panel A. whole sample

Variable	Datastream					Compustat					Differences[29]
	Mean	SD	P1	Median	P99	Mean	SD	P1	Median	P99	(%)
EPS	-5.995	413.1	-139.1	0.285	12.94	-4.441	400.0	-106.3	0.374	10.91	26%
B	57.44	2,664	-28.59	5.628	240.3	55.71	2,619	-19.20	5.548	229.3	3%
CEQ	1,358	6,001	-123.9	124.1	22,253	1,348	6,004	-117.4	119.9	22,205	1%
CSHO	132.0	514.1	0.0280	29.91	1,800	133.5	521.5	0.0300	29.47	1,818	-1%
MV	3,927	18,826	0.530	274.5	71,662	4,059	19,213	0.527	285.1	76,218	-3%
AT	4,109	23,864	0.0710	273.9	58,789	4,123	23,930	0.0690	266.6	59,257	0%
TAC	-0.309	291.3	-19.50	0	15.15	-24.54	4,887	-37.00	0	42.09	-7842%
Obs	40,988					40,988					
Firms	3,850					3,850					

Panel B. 1998 - 2005

Variable	Datastream					Compustat					Differences
	Mean	SD	P1	Median	P99	Mean	SD	P1	Median	P99	(%)
EPS	-11.08	590.0	-332.4	0.252	13.87	-9.513	559.3	-308.4	0.318	13.52	14%
B	104.7	3,682	-56.77	4.759	546.1	116.2	3,631	-31.41	4.837	541	-11%
CEQ	950.4	4,223	-70.63	78.55	15,214	951.5	4,228	-63.73	77.62	15,576	0%
CSHO	130.2	557.3	0.01000	20.77	1,984	127.2	546.4	0.0100	20.63	1,989	2%
MV	3,261	18,293	0.510	164.0	67,732	3,452	18,659	0.516	181.2	73,247	-6%
AT	2,876	17,831	0.127	169.1	39,910	2,900	17,861	0.112	167.6	40,197	-1%
TAC	0.435	457.2	-31.50	0	14.38	8.769	1,116	-80.03	0.00798	73.55	-1916%
Obs	40,988					40,988					
Firms	3,850					3,850					

Table 3.4 compares the descriptive statistics of corporate characteristics between two databases, Compustat and Datastream. Firms' characteristic includes earnings per share (EPS), book value per share (*BVPS*), common equity (*CEQ*), common share outstanding (*CSHO*), market value (*MV*), total assets (*AT*), and total accrual (*TAC*).

[29] Differences is calculated as the percentage differences between the Datastream means and Compustat means (Datastream – Compustat)

Table 3.4. Continued

Panel C. 2006 - 2010

Variable	Datastream					Compustat					Differences (%)
	Mean	SD	P1	Median	P99	Mean	SD	P1	Median	P99	
EPS	-3.108	363.4	-123.5	0.330	13.46	-2.091	386.2	-86.40	0.447	10.99	33%
BVPS	47.29	2,652	-29.29	6.113	224.1	32.27	2,615	-19.04	5.966	176.7	32%
CEQ	1,425	5,918	-117.2	140.7	22,856	1,418	5,921	-114.2	135.6	22,990	0%
CSHO	130.3	492.3	0.0460	30.30	1,727	129.4	484.1	0.0550	30.70	1,698	1%
MV	3,710	16,307	0.470	299.8	64,763	3,763	16,645	0.518	303.4	67,326	-1%
AT	4,157	23,224	0.0790	308.3	55,370	4,184	23,294	0.0740	298.0	56,469	-1%
TAC	-1.279	153.1	-15.97	0	15.33	-97.00	9,040	-37.41	0	51.40	-7484%
Obs	40,988					40,988					
Firms	3,850					3,850					

Panel D. 2011 - 2015

Variable	Datastream					Compustat					Differences (%)
	Mean	SD	P1	Median	P99	Mean	SD	P1	Median	P99	
EPS	-2.899	106.2	-31.57	0.297	11.46	-0.919	64.70	-17.71	0.413	10.12	68%
BVPS	14.90	423.3	-15.45	6.532	84.30	9.938	242.8	-11.09	6.283	68.70	33%
CEQ	1,741	7,490	-264.6	182.1	27,816	1,718	7,494	-223.3	173.6	28,083	1%
CSHO	139.6	504.7	0.276	38.84	1,717	139.2	502.1	0.380	39.55	1,700	0%
MV	4,824	21,161	0.610	441.4	80,862	4,959	21,604	0.537	439.5	88,917	-3%
AT	5,398	29,366	0.0240	406.8	81,046	5,392	29,459	0.0260	394.5	81,812	0%
TAC	-0.308	43.36	-16.19	0	15.38	-0.419	613.5	-17.36	0	19.82	-36%
Obs	40,988					40,988					
Firms	3,850					3,850					

Table 3.5. Sample selection for cross sectional regression model.

Control Variables			
Filter	**Criterion**	**# of Firm-Years**	**# of Unique Firms**
1	All U.S. firms	244,349	24,464
		-526	-203
2	Non-missing data (EPS, B).	243,823	24,261
		-24,474	-979
2	Remove financial firms (Standard Industrial Classification (SIC) codes from 6000 – 6999)	219,349	23,282
		0	0
3	Final sample - winsorized at the 1st and 99th percentile	219,349	23,282

Table 3.5 details the sample selection procedure of all U.S. firms for the RI model. The beginning sample is with all available firms (both dead and alive) in the Compustat database. The starting sample consists of 24,698 firms. After eliminating unavailable and missing data firms, the final sample has 219,349 firm-years and 23,282 unique firms covering the period of 1986 to 2017.

Table 3.6. Data description for cross-sectional model.

Variables	N	Mean	SD	1%	25%	Median	75%	99%
B	219,349	179.8	1,368	0.0157	1.860	5.301	12.20	13,029
EPS	219,349	5.636	57.51	-111.5	-0.130	0.343	1.219	535.2
TAC	219,349	0.356	3.179	-11.58	0	0	0.0162	22.73
NE	219,349	0.324	0.468	0	0	0	1	1
ENE	219,349	-114.4	7,619	-111.5	-0.130	0	0	0

This table reports the summary statistics (the time-series average of mean, median, standard deviation, and particular percentiles) of variables used for the cross-sectional model after dropping extreme and impossible value and being winsorized at the 1% and 99% percentiles. EPS represents the earnings per share which calculated by dividing net income before extraordinary items by number of shares outstanding. NE is the dummy variable that is equal to zero for positive earnings per share and 1 for negative earnings per share. ENE is the interaction terms between E and NE. B is the book value of equity per share of firm i for year t (common equity divided by number of shares outstanding). TAC is the total accruals of firms, calculated using Richardson et al. (2005) definition.

Table 3.7. RI model coefficients

	Years Ahead	Intercept	E	NE	ENE	B	TAC	R-square
1	Coefficient	0.0414	0.695	-1.239	0.198	0.017	-0.0789	0.54
	t-stat	2.62	108.04	-7.75	23.34	31.84	-4.66	
2	Coefficient	0.037	0.614	-2.234	0.254	0.0168	-0.236	0.38
	t-stat	2.53	69.10	-9.98	19.16	29.61	-6.73	
3	Coefficient	-0.0375	0.607	-2.779	0.24	0.0187	-0.373	0.27
	t-stat	-2.43	62.52	-9.77	7.71	8.89	-7.68	
4	Coefficient	-0.133	0.583	-3.122	0.24	0.0223	-0.444	0.22
	t-stat	-4.48	29.75	-11.24	23.68	27.33	-4.64	
5	Coefficient	-0.225	0.615	-3.415	0.126	0.0245	-0.319	0.20
	t-stat	-4.11	37.34	-10.54	12.45	18.24	-6.68	

Table 3.7 reports the average coefficients and t-statistics from the pooled regression for one to five-year ahead earnings per share. For each year from 2003 and 2017, the following model is used to calculate the coefficients with pooled cross-sectional regression and data from the previous ten years:

$$E_{i,t+\tau} = \beta_0 + \beta_1 E_{i,t} + \beta_2 NE_{i,t} + \beta_3 E_{i,t} NE_{i,t} + \beta_4 B_{i,t} + \beta_2 TAC_{i,t} + \varepsilon_{i,t+\tau}$$

where $E_{i,t+\tau}$ ($\tau = 1,2,3,4,5$) represents the earnings per share which calculated by dividing net income before extraordinary items of firm i for year $t+\tau$ by number of shares outstanding. $NE_{i,t}$ is the dummy variable that is equal to zero for positive earnings per share and 1 for negative earnings per share. $E_{i,t}NE_{i,t}$ is the interaction terms between $E_{i,t}$ and $NE_{i,t}$. $B_{i,t}$ is the book value of equity per share of firm i for year t (common equity divided by number of shares outstanding). $TAC_{i,t}$ is the total accruals of firm i for year t and calculated by using Richardson et al. (2005) method which detail can be found in Section 3.4.3.1.

Table 3.8. Summary statistics of earnings forecasts, 2003 – 2017

Period	N	E_{t+1}		E_{t+2}		E_{t+3}		E_{t+4}		E_{t+5}	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
2003 – 2006	3,838	2.207	1.295	1.932	1.153	1.755	1.032	1.645	1.057	1.664	1.123
2007 – 2009	2,276	1.950	1.374	1.700	1.289	1.459	1.231	1.296	1.352	1.437	1.282
2010 – 2017	6,771	2.732	1.939	2.649	1.941	2.561	1.924	2.379	1.924	2.349	1.922
2003 – 2017	15,146	2.334	1.557	2.151	1.493	1.985	1.418	1.837	1.467	1.870	1.473

Table 3.8 summarizes the statistics of one to five years ahead earnings per share forecasts based on the RI model. For each firm and each year in the rated sample (firms rated by at least 2 CRAs), the earnings forecasts for 1 to 5-year ahead (E_{t+1} to E_{t+5}) are estimated by multiplying the coefficients generating from pool cross-sectional regression with the independent variables of the firm in year t.

Table 3.9. Summary statistics of ICC

Panel A. Statistical description of COEC

Variables	No. of obs	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	3,677	60.23	2,113	0.358	391.1	0.115	3.899	6.414	10.25	142.1
ICCPEG	3,413	7.552	16.99	0.422	202.6	0.548	3.390	5.436	8.608	82.61
ICCGLS	10,492	24.02	1,250	0.106	46.61	0.344	4.743	6.451	8.450	22.88
ICCCT	9,841	24.89	1,292	0.341	111.7	0.549	3.521	4.772	6.350	44.27
COEC	10,868	21.78	1,144	0.102	171.9	0.443	4.096	5.469	7.253	54.11

Panel B. Pairwise correlation of ICC measures

	ICCOJ	ICCPEG	ICCGLS	ICCCT	COEC
ICCOJ	1				
ICCPEG	0.7504***	1			
ICCGLS	0.3276***	0.5943***	1		
ICCCT	0.9004***	0.6201***	0.5522***	1	
COEC	0.9439***	0.8109***	0.6902***	0.8917****	1

Table 3.9 shows the summary statistics of the results of the 4 ICC calculation method as well as the average of those 4 in percentage for the initial sample.[30] The results are winsorized 0.5% and 99.5% tail to remove the effect of extreme values. ICCOJ, ICCPEG, ICCGLS and ICCCT is ICC measures calculated using OJ, PEG, GLS and CT method (see Section 3.4.3.2). COEC is the measure of the cost of equity capital, estimated as the average of four ICC measures above. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

[30] The initial sample is the sample before removing missing accounting and rating data, and before winsorizing.

Table 3.10. ICC for different periods

Panel A. Pre-crisis period, 2003 – 2006.

Variables	No. of obs.	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	601	187.7	21.32	0.800	312.6	1.176	3.669	5.480	8.089	90.71
ICCPEG	668	4.600	11.31	0.422	169.3	0.450	2.627	3.895	5.563	21.21
ICCGLS	3,215	39.36	2.808	0.106	37.82	0.461	4.604	6.036	7.508	13.37
ICCCT	3,079	40.16	5.895	0.341	81.34	1.265	3.644	4.594	5.643	15.96
COEC	3,268	38.51	7.185	0.102	95.86	0.761	4.134	5.144	6.358	17.39

Panel B. During crisis period, 2007 – 2009.

Variables	No. of obs.	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	684	118.1	27.91	0.675	391.1	1.398	4.717	7.383	12.86	128.3
ICCPEG	722	9.128	16.47	0.422	202.6	0.479	3.465	5.475	8.912	47.32
ICCGLS	2,150	41.55	5.372	0.106	46.32	0.280	5.699	7.596	10.07	28.16
ICCCT	2,016	43.49	9.990	0.620	109.8	1.696	4.407	5.623	7.726	49.83
COEC	2,225	32.43	11.89	0.102	168.7	0.381	4.920	6.315	8.552	38.99

Panel C. Post-crisis period, 2010 – 2017.

Variables	No. of obs.	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	2,392	11.64	21.64	0.358	326.6	1.286	5.376	8.104	11.86	61.80
ICCPEG	2,023	7.964	13.46	0.422	193.4	0.640	3.838	6.162	9.440	37.36
ICCGLS	5,127	7.059	4.041	0.106	46.61	0.317	4.506	6.392	8.448	17.46
ICCCT	4,746	7.074	6.436	0.341	111.7	0.311	3.070	4.541	6.396	26.85
COEC	5,375	7.210	8.537	0.102	171.9	0.383	3.713	5.389	7.420	31.77

This table shows the summary statistics of the implied cost of equity capital during different periods of time, pre-crisis, during crisis, and post-crisis for the initial sample.

Table 3.11. Summary statistics of ICC for the main regression sample

Panel A. Statistical description of COEC

Variables	No. of obs	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	1,967	8.823	9.882	0.115	73.52	0.115	3.730	6.307	10.26	58.45
ICCPEG	1,758	6.999	5.786	0.548	35.60	0.548	3.386	5.489	8.696	34.03
ICCGLS	6,063	6.829	3.174	0.344	19.36	0.553	4.826	6.482	8.455	18.49
ICCCT	5,756	5.552	3.933	0.549	30.98	0.556	3.572	4.784	6.316	27.36
COEC	6,258	6.614	8.541	0.035	288.4	0.662	4.164	5.506	7.239	29.98

Panel B. Pairwise correlation of ICC measures

	ICCOJ	ICCPEG	ICCGLS	ICCCT	COEC
ICCOJ	1				
ICCPEG	0.7228***	1			
ICCGLS	0.3701***	0.4543***	1		
ICCCT	0.8137***	0.6332***	0.6903***	1	
COEC	0.9103***	0.8468***	0.7665***	0.9138***	1

Table 3.11 shows the summary statistics of the results of the 4 ICC measures as well as the average of those 4 in percentage for the main sample.[31] ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

[31] Main sample is the sample after removing missing accounting and rating observations and after winsorized at the 1st and 99th percentiles to rule out the effect of outliers.

Table 3.12. ICC at different periods for the main regression sample

Panel A. Pre-crisis period, 2003 – 2006.

Variables	No. of obs.	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	273	8.515	10.97	0.968	73.52	1.437	3.734	5.736	8.758	73.52
ICCPEG	303	4.499	3.134	0.548	22.45	0.548	2.629	3.889	5.738	17.11
ICCGLS	1,863	6.290	2.355	0.344	19.36	0.825	4.769	6.148	7.579	13.11
ICCCT	1,817	5.010	2.547	0.549	30.98	1.417	3.747	4.671	5.744	12.64
COEC	1,890	5.709	4.155	0.035	90.71	1.146	4.276	5.270	6.411	15.59

Panel B. During crisis period, 2007 – 2009.

Variables	No. of obs.	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	358	11.41	12.35	0.115	61.11	1.608	4.771	7.553	12.22	43.42
ICCPEG	370	7.675	7.043	0.548	24.19	0.548	3.545	5.491	8.832	18.00
ICCGLS	1,255	8.225	3.734	0.344	19.00	0.468	5.808	7.631	10.05	17.50
ICCCT	1,191	7.011	4.874	0.620	34.94	1.744	4.472	5.677	7.731	30.98
COEC	1,299	7.993	9.056	0.0382	50.95	0.563	5.054	6.402	8.564	37.41

Panel C. Post-crisis period, 2010 – 2017.

Variables	No. of obs.	Mean	St.Dv	Min	Max	1%	25%	50%	75%	99%
ICCOJ	1,421	8.315	8.806	0.115	58.97	0.115	3.540	6.270	10.24	53.44
ICCPEG	1,167	7.407	5.682	0.548	35.60	0.694	3.703	6.089	9.440	35.60
ICCGLS	3,165	6.588	3.194	0.344	23.52	0.456	4.502	6.346	8.411	17.12
ICCCT	2,960	5.337	4.058	0.549	30.98	0.549	3.092	4.519	6.322	26.85
COEC	3,305	6.606	9.889	0.0721	288.4	0.572	3.741	5.366	7.357	30.25

Table 3.12 shows the summary statistics implied cost of equity capital during different periods of time, pre-crisis, during crisis, and post-crisis for the main sample.

Table 3.13. Statistical properties and distributions of annual split ratings

	No. of obs.	Mean	SD	Min	Max	1 CCR (%)	2 CCR (%)	3 CCR (%)	4 CCR (%)	5 CCR (%)	6 CCR (%)	7 - 9 CCR (%)	10 - 12 CCR (%)	> 12 CCR (%)	Split total (%)
Panel A. Absolute split ratings															
Absolute split ratings	6,258	1.982	2.231	0	22	17.6	13.5	21.4	5.1	3.0	4.5	2.1	0.5	0.3	68.0
Panel B. Split ratings															
Moody's – S&P	6,258	-1.012	2.766	-22	22	16.7	12.8	20.8	5.0	2.9	4.5	2.1	0.5	0.3	65.6
Moody's > S&P	1,205	2.363	2.383	1	22	41.1	19.4	28.6	4.7	2.0	1.8	1.6	0.2	0.7	
S&P > Moody's	2,866	3.181	1.988	1	22	19.0	19.6	33.1	8.8	5.5	9.0	3.8	1.0	0.2	

The table presents the descriptive statistics and the distribution of absolute and annual split ratings between Moody's and S&P. Firms' ratings are transformed into number using 58-point comprehensive credit ratings (CCR) scale. Split ratings are computed as daily CCR differences, averaged over the calendar year for each corporation, and rounded to nearest integers. Similar to annual split ratings, absolute split ratings use absolute daily CCR differences to calculate split ratings. 1 CCR (%), …, >=12 CCR (%) columns indicate the magnitudes of split ratings in CCR units. Split total (%) column indicates the percentage of split ratings to the total number of observations.[32]

[32] The reason why split total of absolute split ratings and split ratings are different is that they are calculated by using the average annual split ratings rather than daily split ratings. In fact, both split total figures will be the same if they are based on daily split ratings.

Table 3.14. Statistical properties and distributions of annual split ratings for three sub-periods.

	No. of obs.	Mean	SD	Min	Max	1 CCR (%)	2 CCR (%)	3 CCR (%)	4 CCR (%)	5 CCR (%)	6 CCR (%)	7- 9 CCR (%)	10 - 12 CCR (%)	> 12 CCR (%)	Split total (%)
Panel A. Absolute split ratings															
2003-2006	1,795	2.559	2.445	0	22	15.9	15.9	20.3	7.0	5.3	7.3	3.8	1.1	0.7	77.0
2007-2009	812	1.721	2.031	0	13	20.6	14.2	21.3	3.5	2.2	3.2	1.2	0.2	0.2	66.4
2010-2017	3,221	1.756	2.114	0	22	17.3	11.9	22.0	4.6	2.1	3.4	1.4	0.3	0.2	63.0
Panel B. Split ratings															
2003-2006	1,795	-1.770	3.001	-22	16	16.1	14.6	19.8	6.9	5.1	7.2	3.7	1.0	0.4	74.9
2007-2009	812	-0.693	2.544	-13	22	18.5	13.6	20.6	3.5	2.1	3.2	1.2	0.2	0.2	62.9
2010-2017	3,221	-0.704	2.620	-13	22	16.4	11.4	21.5	4.5	2.0	3.4	1.4	0.3	0.2	61.1

Table 3.14 presents the descriptive statistics and the distribution of absolute and annual split ratings between Moody's and S&P for three different sub-periods pre-crisis 2003-2006, crisis 2007-2009, and post-crisis 2010-2017. Firms' ratings are transformed into number using 58-point comprehensive credit ratings (CCR) scale. Split ratings are computed as daily CCR differences, averaged over the calendar year for each corporation, and rounded to nearest integers. Similar to split ratings, absolute split ratings use absolute daily CCR differences to calculate split ratings. 1 CCR (%), …, >=12 CCR (%) columns indicate the magnitudes of split ratings in CCR units. Split total (%) column indicates the percentage of split ratings to the total number of observations.

Table 3.15. Summary statistics of control variables, 2002 – 2017

Panel A: Control variables statistics

Variables	No. of obs	Mean	St.Dv	Min	Max	1%	25%	Median	75%	99%
ROE	6,258	0.158	1.432	-22.04	22.29	-1.554	0.060	0.141	0.230	2.217
D2A	6,258	0.319	0.163	0.000	1.139	0.018	0.200	0.297	0.414	0.764
BM	6,258	0.515	4.946	-186.3	248.1	0.004	0.266	0.423	0.639	2.179
STDNI	6,258	0.013	0.017	0.001	0.096	0.001	0.004	0.007	0.013	0.096
BETA	6,258	1.240	0.728	-0.479	4.508	-0.152	0.766	1.153	1.590	3.786
IDIO	6,258	9.267	7.676	2.641	156.7	2.738	5.643	7.758	10.85	32.46

Panel B: Correlations between control variables.

	ASPLIT	ROE	D2A	BM	BETA	STDNI	IDIO
ASPLIT	1						
ROE	-0.0374***	1					
D2A	0.0423***	-0.0747***	1				
BM	0.0374***	-0.3717***	0.0483***	1			
BETA	-0.0195	-0.1425***	-0.0396***	0.1778***	1		
STDNI	0.0105	-0.2421***	0.0239*	0.1314***	0.2512***	1	
IDIO	0.0767***	-0.2415***	0.0934***	0.3412***	0.4603***	0.3723***	1

Table 3.15 reports the summary statistics of control variables and the pairwise correlation between control variables. *ROE* is the return on equity calculated as net income before extraordinary items and preferred dividend divided by common equity. *D2A* is the financial leverage ratio of total debt to total assets. *BM* is the ratio between book value of common equity and market value of common equity. *BETA* is calculated using monthly returns over the last 60 months. *STDNI* is the standard deviation of quarterly net income over quarterly total assets measured over the previous two years. *IDIO* is the standard deviation of the previous year's monthly returns. All variables are winsorized at 1% and 99% to remove the effect of outliers. *** p<0.01, ** p<0.05, * p<0.1

Table 3.16. Cost of Equity Capital

Variables	Expected sign	COEC	
		(I)	(II)
ASPLIT	+	0.138**	
		(2.12)	
ASPLIT_DUMMY	+		0.539***
			(3.17)
ROE	-	-0.271**	-0.271**
		(-2.32)	(-2.31)
D2A	+	2.241*	2.227*
		(1.70)	(1.69)
BM	-	-0.051	-0.051
		(-0.29)	(-0.29)
BETA	+	0.050	0.041
		(0.23)	(0.18)
STDNI	+	61.07***	60.76***
		(5.58)	(5.57)
IDIO	+	-0.005	-0.005
		(-0.15)	(-0.15)
Constant		27.489**	27.303**
		(2.23)	(2.22)
Rating Level		Yes	Yes
Year*Industry		Yes	Yes
Observations		6,237	6,237
Adjusted R-squared		0.071	0.072

Table 3.16 reports the cost of equity capital regression results using Eq. (3.1). The dependent variable is the cost of equity capital in percentage. *ASPLIT* is the absolute annual split ratings. *ASPLIT_DUMMY* is a dummy variable which equals to 1 if a firm is split rating (*ASPLIT* > 0) and 0 otherwise. The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book-to-market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*) and idiosyncratic risk (*IDIO*), see Table 3.2 for more detailed definitions. Rating level and Year*Industry interactions are included in the regressions. Numbers in parentheses are robust t-statistics. Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

Table 3.17. Cross-sectional tests

Variables	Expected sign	Small vs Large (I)	Investment vs Speculative (II)	Crisis vs No-Crisis (III)
ASPLIT×SMALL	+	0.312***		
		(3.41)		
ASPLIT×(1 – *SMALL*)	+	-0.056		
		(-0.67)		
ASPLIT×INVST	+		0.080	
			(0.97)	
ASPLIT×(1 – *INVST*)	+		0.211**	
			(1.98)	
ASPLIT×CRISIS	+			0.374**
				(2.05)
ASPLIT×(1 – *CRISIS*)	+			0.082
				(1.22)
ROE	-	-0.265**	-0.273**	-0.272**
		(-2.26)	(-2.33)	(-2.33)
D2A	+	2.144	2.231*	2.234*
		(1.63)	(1.70)	(1.70)
BM	-	-0.051	-0.051	-0.051
		(-0.29)	(-0.29)	(-0.29)
BETA	+	0.059	0.057	0.046
		(0.26)	(0.26)	(0.20)
STDNI	+	61.24***	61.29***	61.14***
		(5.59)	(5.61)	(5.59)
IDIO	+	-0.006	-0.005	-0.005
		(-0.20)	(-0.18)	(-0.17)
Constant		26.959**	27.066**	27.628**
		(2.19)	(2.20)	(2.24)
ΔCOEF		0.368***	-0.131	0.292
		(9.86)	(0.91)	(2.29)
Rating Level		Yes	Yes	Yes
Year*Industry		Yes	Yes	Yes
Observations		6,237	6,237	6,237
Adjusted R-squared		0.072	0.071	0.071

Table 3.17 reports the cost of equity capital regression results using Eq. (3.1) with three different sets of interaction terms, *ASPLIT×SMALL*, *ASPLIT*×(1 – *SMALL*), *ASPLIT×INVST*, *ASPLIT*×(1 – *INVST*), *ASPLIT×CRISIS* and *ASPLIT*×(1 – *CRISIS*). The dependent variable is the cost of equity capital in percentage. *ASPLIT* is the absolute annual split ratings. *SMALL* is a dummy that identifies firms with below-sample-median value of firm size (*FS*); *INVST* is a dummy that identifies firms with an investment-grade rating; *CRISIS* is a dummy that identifies the crisis period (2007 – 2009). The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book-to-market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*) and idiosyncratic risk (*IDIO*), see Table 3.2 for more detailed definitions. Rating level and Year*Industry interactions are included in the regressions. The test of the differences between two interaction terms is presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (F-test for ΔCOEF). Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

Table 3.18 Matching quality tests for NN matching with replacement and the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched / Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|
IDIO	U	9.568	8.063	25.7		8.86	0
	M	9.040	9.136	-1.6	93.6	-0.89	0.371
D2A	U	0.473	0.440	13.7		5.26	0
	M	0.468	0.480	-4.9	64.1	-1.61	0.108
TAXES	U	0.018	0.025	-22		-8.19	0
	M	0.020	0.019	3.7	83.4	1.49	0.136
FS	U	8.380	8.898	-38.4		-14.35	0
	M	8.452	8.478	-2	94.9	-0.9	0.366
MTB	U	1.305	1.409	-13.7		-5.16	0
	M	1.320	1.346	-3.5	74.7	-1.55	0.122

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
COEC	Unmatched	6.801	6.011	0.790	0.219	3.61
	ATT	6.769	6.301	0.469	0.205	2.29

Panel C. Pseudo R-square test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.088	702.49	0.000	4.9	3.2	72.0*	1.06	71
Matched	0.021	119.89	0.636	2.3	2.1	34.6*	1.06	43

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the *ASPLIT_DUMMY* variable, which equals one if firms are split rated and zero otherwise. The interested covariates are idiosyncratic risk (*IDIO*), firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*) and taxes over total assets ratio (*TAXES*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R-square and the joint significance tests.

Table 3.19 Main regression using a matched sample (NN matching)

Variables	Expected Sign	Probit Model (I)	COEC (II)	COEC (III)
ASPLIT	+		0.133**	
			(2.30)	
ASPLIT_DUMMY	+			0.543***
				(2.82)
ROE	-		-0.323**	-0.323**
			(-2.31)	(-2.31)
D2A	+	0.034	4.608***	4.598***
		(0.42)	(4.04)	(4.03)
BM	+		2.486***	2.481***
			(5.62)	(5.60)
BETA	-		-0.161	-0.168
			(-0.79)	(-0.83)
STDNI	+		53.06***	52.94***
			(4.52)	(4.51)
IDIO	+	0.024***	0.091***	0.091***
		(4.91)	(2.68)	(2.68)
TAXES	-	-3.22***		
		(-4.87)		
FS	-	-0.070***		
		(-3.54)		
MTB	-	-0.018		
		(-0.62)		
Constant		-0.500	5.803	5.763
		(0.63)	(1.45)	(1.44)
Rating Level		Yes	Yes	Yes
Year*Industry		Yes	Yes	Yes
Observations		6,317	7,782	7,782
Adjusted R-squared			0.116	0.117
Pseudo R-squared		0.088		

Table 3.19 reports the propensity score estimation model (Column (I)) and the cost of equity capital regression results using Eq. (3.1) and the matched sample (Column (II) and (III)). The dependent variable for Column (I) is *ASPLIT_DUMMY* and for Column (II) and (III) is the cost of equity capital in percentage (COEC). *ASPLIT* is the absolute annual split ratings. *ASPLIT_DUMMY* is a dummy variable which equals to 1 if a firm is split rating (*ASPLIT* > 0) and 0 otherwise. The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book to market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*), idiosyncratic risk (*IDIO*) firm size (*FS*), market to book ratio (*MTB*) and taxes ratio (*TAXES*), see Table 3.2 for more detailed definitions. Rating level and Year*Industry interactions are included in the regressions. Numbers in parentheses are robust t-statistics. Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

Table 3.20. Superior S&P versus superior Moody's ratings.

Variables	Expected sign	COEC (I)	COEC (II)
SUP_MOODY	+	1.034***	
		(2.91)	
SUP_S&P	+	0.299	
		(1.61)	
SUP_MOODY_CCR	+		0.174**
			(2.22)
SUP_S&P_CCR	+		-0.018
			(-0.33)
ROE	-	-0.272**	-0.270**
		(-2.33)	(-2.31)
D2A	+	2.204*	2.236*
		(1.68)	(1.70)
BM	-	-0.052	-0.053
		(-0.30)	(-0.30)
BETA	+	0.042	0.052
		(0.19)	(0.23)
STDNI	+	60.246***	60.443***
		(5.53)	(5.49)
IDIO	+	-0.005	-0.004
		(-0.17)	(-0.14)
Constant		27.381**	27.664**
		(2.22)	(2.25)
ΔCOEF		0.733*	0.192**
		(3.45)	(4.13)
Rating Level		Yes	Yes
Year*Industry		Yes	Yes
Observations		6,237	6,237
Adjusted R-squared		0.072	0.071

Table 3.20 reports the cost of equity capital regression results using Eq. (3.2) and Eq. (3.3). The dependent variable is the cost of equity capital in percentage. *ASPLIT* is the absolute annual split ratings. *ASPLIT_DUMMY* is a dummy variable which equals to 1 if a firm is split rating (*ASPLIT* > 0) and 0 otherwise. The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book-to-market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*) and idiosyncratic risk (*IDIO*), see Table 3.2 for more detailed definitions. Rating level and Year*Industry interactions are included in the regressions. Numbers in parentheses are robust t-statistics. Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

Table 3.21. Summary of the key findings of Chapter 3.

Research questions	Equations, hypotheses and tables	Findings
What is the impact of split ratings on the cost of equity capital?	Hypothesis 1 Equation (3.1) Table 3.16	Split rated firms have a higher cost of equity capital than non-split rated firms with similar credit risk. Firms with one-notch split ratings have a higher cost of equity capital by about 42 basis points. This suggests that equity investors price split ratings when assessing firms' expected return.
Is the impact of superior ratings from Moody's on the cost of equity capital different from the impact of superior ratings from S&P?	Hypothesis 2 Equation (3.2) Table 3.20	Firms with superior Moody's ratings have a significantly higher cost of equity capital compared to firms with superior S&P ratings, suggesting that equity investors place more weight on S&P ratings when assessing firms' cost of equity capital.
Cross-sectional tests	Small vs large firms. Investment-grade vs speculative-grade firms. Crisis vs non-crisis periods. Table 3.17	The effect of split ratings on the cost of equity capital is predominantly associated with small firms and firms with speculative ratings. The effect of split ratings on the cost of equity capital is stronger during the crisis period.
Endogeneity investigation	Propensity score matching (PSM) with various matching methods. Tables 3.18, 3.19, 3.B.1, 3.B.2, 3.B.3 and 3.B.4.	Results from PSM approaches are consistent with the results of baseline models (using OLS estimation), suggesting that the main results are unlikely to suffer from endogeneity issues. By the nature of the matching process, the results of PSM models suggest that the effect on the cost of equity capital is derived from the information asymmetry driven by split ratings rather than other sources of information asymmetry (e.g., covariates such as idiosyncratic risk, taxes and firm size).
Additional robustness test	Excluding missing total accruals (TAC) Table 3.B.5	The results based on the exclusion of missing TAC are consistent with the baseline results.

Appendix 3.A: Matching methods

Matching methods

This Section presents various propensity matching methods, namely, nearest neighbour matching, caliper matching, radius matching, kernel matching and Mahalanobis metric matching. Each matching method has its own advantage and disadvantages.

Nearest neighbour matching

Nearest neighbour (NN) matching is one of the basic, easy to understand and implement methods of matching propensity score (Rubin, 1973). In the simplest form, 1:1 NN matching, unit *i* in the treatment group is matched with unit *j* in the control group if the absolute distance between the propensity of unit *i* and unit *j* are minimum.

$$d(i,j) = min_j\{\left|e(\mathbf{X}_i) - e(\mathbf{X}_j)\right|\} \tag{3.13}$$

In this method, the treatment and control unit are randomly ordered. There are two variants of NN matching, “with replacement” and “without replacement”. In “With replacement” NN matching, an untreated unit is used as a match for more than one time, while in “without replacement” NN matching, the untreated unit is only allowed to match with one treated unit. “with replacement” matching is helpful when there are fewer control units comparable to the treated units (Dehejia and Wahba, 1999). The decision of choosing to match with replacement or without replacement is the trade-off between bias and variance. Matching with replacement reduces the bias by increasing the average quality of matching but increases the variance of the estimators (Smith and Todd, 2005).

Another variant of NN matching is to use more than one nearest neighbour for the treated unit. The trade-off of using more than one NN matching is between reduced variance by using more information to construct the control groups and increased bias by including poorer matches.

Caliper matching and radius matching

One issue with NN matching is that bad matches could happen if the nearest neighbour is far away from the treated unit. This problem could be avoided by setting a tolerance level on the maximum propensity score distance that could be accepted (caliper) (Rosenbaum and Rubin, 1985b). Thus, in caliper matching, a treated unit *i* will be matched with a control unit *j* if the distance between propensity score of unit i and unit j is the smallest distance within an caliper band, b:

$$d(i,j) = min_j\{\left|e(\mathbf{X}_i) - e(\mathbf{X}_j)\right| < b\} \tag{3.14}$$

Thus, by imposing a threshold to the maximum propensity score distance, the quality of matches is improved as bad matches are avoided. However, since the number of matches is limited, the variance of estimates will increase. Another possible disadvantage of caliper matching is that there is no rational guide to choose the tolerance level (Smith and Todd, 2005). The lower caliper band, the better matching quality but the fewer performed matches. In this Chapter, caliper band is set at 0.01, which indicates that the tolerance level on the maximum propensity scored distance to not exceed 1% in absolute value (Khatami et al., 2016). Using low level of caliper results in a greater precision matching and thus better potential bias reduction (Li and Zaiats, 2017). Since the number of observations in the sample is sufficient enough, the effect of small caliper band on variance is minimized.

A variant of caliper matching, radius matching, is suggested by Dehejia and Wahba (2002). In caliper matching, treated unit and control unit are matched in one-to-one basis/the nearest neighbour basis, that is one treated unit is paired with one nearest or closest non-treated/control unit. On the other hand, in radius matching, the one-to-many matching is imposed, that is treated unit are matched with multiple control units if the propensity score distance of those control units to treated unit satisfies the tolerance level/caliper band, *b*.

The advantage of this method is that it has the benefit of caliper matching, that is avoiding bad matches, but also shares the attractive feature of multiple NN matching, that is reducing variance of the estimates by using extra good matches within the caliper band.

Kernel matching

For NN matching, caliper matching or radius matching, the number of used control units is limited to the unit in the control group that matches the unit in the treatment group. Kernel matching, however, is a non-parametric matching estimator that the counterfactual outcome is constructed by using weighted of all units in the control group (Heckman et al., 1997). The weights of control units are estimated using the kernel function and the bandwidth parameter and depending on the distance between the control unit and the treated unit, such that the closer a control unit to treated unit in terms of propensity score, the higher the weight and vice versa (Pan and Bai, 2015).

$$w_{ij} = \frac{K\left(\frac{e(\mathbf{X}_j) - e(\mathbf{X}_i)}{h}\right)}{\sum_{l=1}^{N_0} K\left(\frac{e(\mathbf{X}_l) - e(\mathbf{X}_i)}{h}\right)} \tag{3.15}$$

where $K()$ is a kernel function, e.g. the Gaussian kernel, the biweight kernel, the Epanechnikov kernel, the uniform kernel and the tricube kernel. h is the bandwidth for kernel. N_0 is the total numbers of control units. The choice of bandwidth h is the trade-off between the small variance and an unbiased estimate of the true density function. High bandwidth level results in a smoother estimate density function and therefore lesser variance between the estimated and the true density function; however, smoother estimate density function could also lead to a biased estimate of the true density function (Caliendo and Kopeinig, 2008).

Overall, the main advantage of kernel matching is the lower variance achieved by using all available information but at the same time facing the risk of including bad matches by doing so.

Mahalanobis matching

Another matching method for propensity score analysis is Mahalanobis matching (Rosenbaum and Rubin, 1985a; Rubin and Thomas, 2000; Guo et al., 2006). Mahalanobis metric (caliper) matching method matches each treated unit *i* to a closet Mahalanobis distance control unit *j*, $d(i, j)$.

$$\begin{gathered} d(i,j) = \ min_j\{D_{ij}\} \\ D_{ij} = (V_i - V_j)^T C^{-1} (V_i - V_j) \end{gathered} \tag{3.16}$$

where $V_\bullet$ ($\bullet$ = *i* or *j*) is the value of $\{\mathbf{X}_\bullet^T, e(\mathbf{X}_\bullet)\}^T$ and *C* is the sample variance-covariance matrix of $\{\mathbf{X}_\bullet^T, e(\mathbf{X}_\bullet)\}$ (Pan and Bai, 2015).

Similar to caliper matching, Mahalanobis caliper matching uses a tolerance level, caliper band, to limit the maximum Mahalanobis distance between unit in the control group and unit in the treatment group.

$$d(i,j) = \ min_j\{D_{ij} < b\} \tag{3.17}$$

Overall, none of the propensity matching methods is superior to the others. The choice of each method base on the trade-off between bias and variance. The performance of different matching methods depends on the structure of the data. If there are only a few control units, it would be better to match with replacement. On the other hand, if there are more than one comparable control units, oversampling (multiple neighbours/with replacement) or kernel matching can be used to gain more precision.

Appendix 3.B: Additional robustness tests

Table 3.B.1 Matching quality tests for radius matching with the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
IDIO	U	9.568	8.063	25.7		8.86	0
	M	8.898	8.986	-1.5	94.2	-0.8	0.421
D2A	U	0.473	0.440	13.7		5.26	0
	M	0.463	0.473	-4	70.9	-1.37	0.17
TAXES	U	0.018	0.025	-22		-8.19	0
	M	0.020	0.020	2.2	89.9	0.92	0.357
FS	U	8.380	8.898	-38.4		-14.35	0
	M	8.498	8.495	0.2	99.4	0.11	0.914
MTB	U	1.305	1.409	-13.7		-5.16	0
	M	1.328	1.340	-1.6	88.2	-0.71	0.476

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
COEC	Unmatched	6.801	6.011	0.790	0.219	3.61
	ATT	6.728	6.240	0.488	0.193	2.53

Panel C. Pseudo R-square test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.088	698.250	0.000	4.9	3.2	71.7	1.06	60
Matched	0.007	68.490	1.000	1.4	1.3	19.2	0.98	40

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the *ASPLIT_DUMMY* variable, which equals one if firms are split rated and zero otherwise. The interested covariates are idiosyncratic risk (*IDIO*), firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*) and taxes over total assets ratio (*TAXES*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R-square and the joint significance tests.

Table 3.B.2 Main regression using a matched sample (radius matching)

Variables	Expected Sign	Probit Model (I)	COEC (II)	COEC (III)
ASPLIT	+		0.160**	
			(2.18)	
ASPLIT_DUMMY	+			0.493**
				(2.44)
ROE	-		-0.376**	-0.375**
			(-2.47)	(-2.46)
D2A	+	0.034	4.211***	4.200***
		(0.42)	(3.76)	(3.76)
BM	+		2.135***	2.129***
			(4.05)	(4.04)
BETA	-		-0.117	-0.124
			(-0.54)	(-0.57)
STDNI	+		54.90***	54.82***
			(4.81)	(4.81)
IDIO	+	0.025***	0.117**	0.118**
		(4.91)	(2.53)	(2.54)
TAXES	-	-3.18***		
		(-4.80)		
FS	-	-0.070***		
		(-3.54)		
MTB	-	-0.018		
		(-0.62)		
Constant		-0.506	3.538	3.537
		(-0.49)	(1.09)	(1.09)
Rating Level		Yes	Yes	Yes
Year*Industry		Yes	Yes	Yes
Observations		6,318	5,488	5,488
Adjusted R-squared			0.093	0.093
Pseudo R-squared		0.088		

Table 3.B.2 reports the propensity score estimation model (Column (I)) and cost of equity capital regression results using Eq. (3.1) and the matched sample (Column (II) and (III)). The dependent variable for Column (I) is *ASPLIT_DUMMY* and for Column (II) and (III) is the cost of equity capital in percentage (COEC). *ASPLIT* is the absolute annual split ratings. *ASPLIT_DUMMY* is a dummy variable which equals to 1 if a firm is split rating (*ASPLIT* > 0) and 0 otherwise. The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book to market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*), idiosyncratic risk (*IDIO*), firm size (*FS*), market to book ratio (*MTB*) and taxes ratio (*TAXES*), see Table 3.2 for more detailed definitions. Rating level and Year*Industry interactions are included in the regressions. Numbers in parentheses are robust t-statistics. Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

Table 3.B.3 Matching quality tests for kernel matching with the bandwidth of 0.06.

Panel A. Standardised bias test

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|
IDIO	U	9.568	8.063	25.7		8.86	0
	M	9.568	9.389	3.1	88.1	1.28	0.199
D2A	U	0.473	0.440	13.7		5.26	0
	M	0.473	0.481	-3.2	76.4	-1.08	0.279
TAXES	U	0.018	0.025	-22		-8.19	0
	M	0.018	0.017	2.7	87.6	1.11	0.268
FS	U	8.380	8.898	-38.4		-14.35	0
	M	8.380	8.421	-3.1	91.9	-1.45	0.146
MTB	U	1.305	1.409	-13.7		-5.16	0
	M	1.305	1.325	-2.6	80.8	-1.26	0.209

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
COEC	Unmatched	6.801	6.011	0.790	0.219	3.61
	ATT	6.801	6.295	0.506	0.179	2.82

Panel C. Pseudo R-square test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.088	698.25	0	4.9	3.2	71.7	1.06	60
Matched	0.005	64.32	1	1.1	0.8	17.3	1.32	60

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the *ASPLIT_DUMMY* variable, which equals one if firms are split rated and zero otherwise. The interested covariates are idiosyncratic risk (*IDIO*) firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*) and taxes over total assets ratio (*TAXES*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R-square and the joint significance tests.

Table 3.B.4 Main regression using a matched sample (kernel matching)

Variables	Expected Sign	Probit Model (I)	COEC (II)	COEC (III)
ASPLIT	+		0.140**	
			(2.08)	
ASPLIT_DUMMY	+			0.425**
				(2.26)
ROE	-		-0.325***	-0.321***
			(-2.70)	(-2.65)
D2A	+	0.034	4.425***	4.407***
		(0.42)	(4.33)	(4.32)
BM	+		1.553***	1.546***
			(3.96)	(3.92)
BETA	-		-0.022	-0.047
			(-0.12)	(-0.26)
STDNI	+		60.19***	59.63***
			(6.00)	(5.93)
IDIO	+	0.025***	0.022	0.023
		(4.91)	(0.85)	(0.88)
TAXES	-	-3.22***		
		(-4.87)		
FS	-	-0.070***		
		(-3.54)		
MTB	-	-0.018		
		(-0.62)		
Constant		-0.506	0.020	0.144
		(-0.49)	(0.01)	(0.07)
Rating Level		Yes	Yes	Yes
Year*Industry		Yes	Yes	Yes
Observations		6,318	6,150	6,150
Adjusted R-squared			0.107	0.107
Pseudo R-squared		0.088		

Table 3.B.4 reports the propensity score estimation model (Column (I)) and cost of equity capital regression results using Eq. (3.1) and the matched sample (Column (II) and (III)). The dependent variable for Column (I) is *ASPLIT_DUMMY* and for Column (II) and (III) is the cost of equity capital in percentage (COEC). *ASPLIT* is the absolute annual split ratings. *ASPLIT_DUMMY* is a dummy variable which equals to 1 if a firm is split rating (*ASPLIT* > 0) and 0 otherwise. The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book to market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*), idiosyncratic risk (*IDIO*) firm size (*FS*), market to book ratio (*MTB*) and taxes ratio (*TAXES*), see Table 3.2 for more detailed definitions. Rating level and Year*Industry interactions are included in the regressions. Numbers in parentheses are robust t-statistics. Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

Table 3.B.5 Cost of Equity Capital without setting missing *TAC* to 0.

Variables	Expected sign	COEC2	
		(I)	(II)
ASPLIT	+	0.104**	
		(2.00)	
ASPLIT_DUMMY	+		0.539***
			(3.17)
ROE	-	-0.072	-0.071
		(-1.10)	(-1.09)
D2A	+	0.192	0.192
		(0.23)	(0.23)
BM	-	0.116	0.116
		(0.67)	(0.67)
BETA	+	0.063	0.060
		(0.37)	(0.35)
STDNI	+	35.522***	35.409***
		(4.75)	(4.74)
IDIO	+	-0.002	-0.002
		(-0.07)	(-0.06)
Constant		23.864**	23.944**
		(2.15)	(2.15)
Rating Level		Yes	Yes
Year*Industry		Yes	Yes
Observations		4,934	4,934
Adjusted R-squared		0.161	0.161

Table 3.B.5 reports the main regression results using Eq. (3.1) and using a new COEC generated without setting missing *TAC* to 0. The dependent variable is the cost of equity capital (COEC2) in percentage. *ASPLIT* is the absolute annual split ratings. *ASPLIT_DUMMY* is a dummy variable which equals to 1 if a firm is split rating (*ASPLIT* > 0) and 0 otherwise. The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book-to-market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*) and idiosyncratic risk (*IDIO*), see Table 3.2 for more detailed definitions. Rating level and Year*Industry interactions are included in the regressions. Numbers in parentheses are robust t-statistics. Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5% and 10% levels, respectively.

Appendix 3.C: Compustat data definitions

Compustat item	Definition
act	Total current assets, represents cash and other assets, which, in the next 12 months, expect to be realised in cash or used in the production of revenue.
at	Total assets, the total assets/liabilities of a company at a point in time.
atq	Quarterly total assets
bvps	Book value per share, based upon the fiscal year-end data.
ceq	Total common equity, this item represents the common shareholders' interest in the company.
che	Cash and short-term investment, cash and all securities readily transferable to cash as listed in the current asset section.
csho	Common shares outstanding, represents the net number of all common shares outstanding at year-end for the annual file, and as of the Balance Sheet date for the quarterly file excluding treasury shares and scrip.
dlc	Debt in current liabilities represents the total amount of short-term notes and the current portion of long-term debt that is due in one year.
dltt	Total long-term debt represents debt obligations due more than one year from the company's Balance Sheet date or due after the current operating cycle.
ib	Income before extraordinary items, represents the income of a company after all expenses, include special items, income taxes, and minority interest – but before provisions for common and/or preferred dividends.
ibq	Quarterly income before extraordinary items.
ivao	Investment and advances, represents long-term receivables and other investments, and advances including investments in affiliated companies, unconsolidated subsidiaries, and joint ventures in which no equity in earnings has yet been incurred.
ivst	Short-term investments, represents currently marketable investments as presented in the current asset section of the Balance Sheet.
lct	Total current liabilities, represents liabilities due within one year, including current portion of long-term debt.
lt	Total liabilities, current liabilities plus long-term debt plus other liabilities plus deferred taxes and investment tax credit plus minority interest.
ppent	Total (gross) property, plant and equipment represents the cost of fixed property of a company used in the production of revenue before adjustments for accumulated depreciation, depletion, and amortization.
prccm	Price close monthly.
prcc_f	Price close at the end of the fiscal year.
pstk	Preferred stock – carrying value, the par or stated value of preferred stock.
pstkl	Preferred stock – liquidating value, the total dollar value of the net number of preferred shares outstanding in the event of involuntary liquidation.
trfm	Monthly total return factor.
txditc	Deferred taxes and investment tax credit, the accumulated differences between income expense for financial statements and tax forms due to timing differences and investment tax credit.

Appendix 3.D. Superior Rating Model, Inferior Rating Model and the Cost of Equity Capital

Following Livingston and Zhou (2010), two regression models are used to separate the impact of split ratings (information risk) and credit rating levels (credit risk) on firms' cost of equity capital.

The amended regression models replace *LEVEL* (which is calculated as the rounded average between Moody's and S&P ratings (20-unit scale)). Instead, in the first model, superior ratings between the two CRAs are used to create the rating dummy variables: SUP_LEVEL_k (*k* = 1 to 19). In this model, the *ASPLIT_DUM* variable reflects the fact that a split rated firm has an inferior rating not captured by the rating dummy variables.

$$\begin{aligned} COEC_{i,t} = {} & \beta_0 + \beta_S ASPLIT\_DUM_{i,t} \\ & + \gamma_j \sum_{j=1}^{n} CONTROL_{i,j,t} + \lambda_k \sum_{k=1}^{19} SUP\_LEVEL_{i,k,t} \\ & + \varphi_l \sum_{l=1}^{15} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \end{aligned} \tag{3.D.1}$$

If investors assess firms' cost of equity capital based on the superior ratings alone and the inferior rating has no impact, β_S should be insignificant. Alternatively, if equity investors consider inferior ratings as well, β_S should be positive and significant as inferior ratings convey additional negative information. Thus, β_S could be interpreted as the difference between the cost of equity capital of split rated firms and the estimated cost of equity capital of these firms if both CRAs had assigned the same superior rating.

In the second model, the inferior ratings between the two CRAs are used to create the rating dummy variables: INF_LEVEL_k (*k* = 1 to 19). In this model, the *ASPLIT_DUM* variable reflects the fact that a split rated firm has a superior rating not captured by the rating dummy variables.

$$COEC_{i,t} = \beta_0 + \beta_I ASPLIT\_DUM_{i,t} + \gamma_j \sum_{j=1}^{n} CONTROL_{i,j,t} + \lambda_k \sum_{k=1}^{19} INF\_LEVEL_{i,k,t} + \varphi_l \sum_{l=1}^{15} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \quad (3.D.2)$$

If firms' cost of equity capital is decided based on the inferior ratings alone and the superior rating has no impact, β_I should be insignificant. Alternatively, if equity investors consider inferior ratings as well, β_I should be negative and significant as superior ratings convey additional positive information. However, if equity investors consider the information risk arising from split ratings above and beyond credit risk, β_I should be positive and significant. Thus, β_I could be interpreted as the difference between the cost of equity capital of split rated firms and the estimated cost of equity capital of these firms if both CRAs had assigned the same inferior rating.

Let *D* be the actual cost of equity capital of split rated firms and S(I) be the estimated cost of equity capital if both CRAs had assigned the same superior (inferior) ratings. Then, there are three possible scenarios as illustrated in Figure 3.D.1,

$$\begin{aligned} S &= D - |\beta_S|;\ I = D - |\beta_I| \ if\ S < I < D \\ S &= D - |\beta_S|;\ I = D + |\beta_I| \ if\ S < D < I \\ S &= D + |\beta_S|;\ I = D + |\beta_I| \ if\ D < S < I \end{aligned} \quad (3.D.3)$$

The difference between the long-term debt level for the superior rating case and that for inferior rating is:

$$\begin{aligned} I - S &= |\beta_S| - |\beta_I| \ if\ S < I < D \\ I - S &= |\beta_S| + |\beta_I| \ if\ S < D < I \\ I - S &= |\beta_I| - |\beta_S| \ if\ D < S < I \end{aligned} \quad (3.D.4)$$

Let *A* be the average of *S* and *I*,

$$A = \frac{I + S}{2} = D - \frac{|\beta_S| + |\beta_I|}{2} \ if\ S < I < D \quad (3.D.5)$$

$$A = \frac{I + S}{2} = D - \frac{|\beta_S| - |\beta_I|}{2} \ if\ S < D < I$$

$$A = \frac{I + S}{2} = D + \frac{|\beta_S| + |\beta_I|}{2} \; if \; D < S < I$$

The impact of information risk of split ratings on firms' debt maturity decisions is:

$$INFO\_RISK = D - A = D - \left(D - \frac{|\beta_S| + |\beta_I|}{2}\right) = \frac{|\beta_S| + |\beta_I|}{2} \; if \; S < I < D \quad (3.D.6)$$

$$INFO\_RISK = D - A = D - \left(D - \frac{|\beta_S| - |\beta_I|}{2}\right) = \frac{|\beta_S| - |\beta_I|}{2} \; if \; S < D < I$$

$$INFO\_RISK = D - A = D - \left(D + \frac{|\beta_S| + |\beta_I|}{2}\right) = -\frac{|\beta_S| + |\beta_I|}{2} \; if \; D < S < I$$

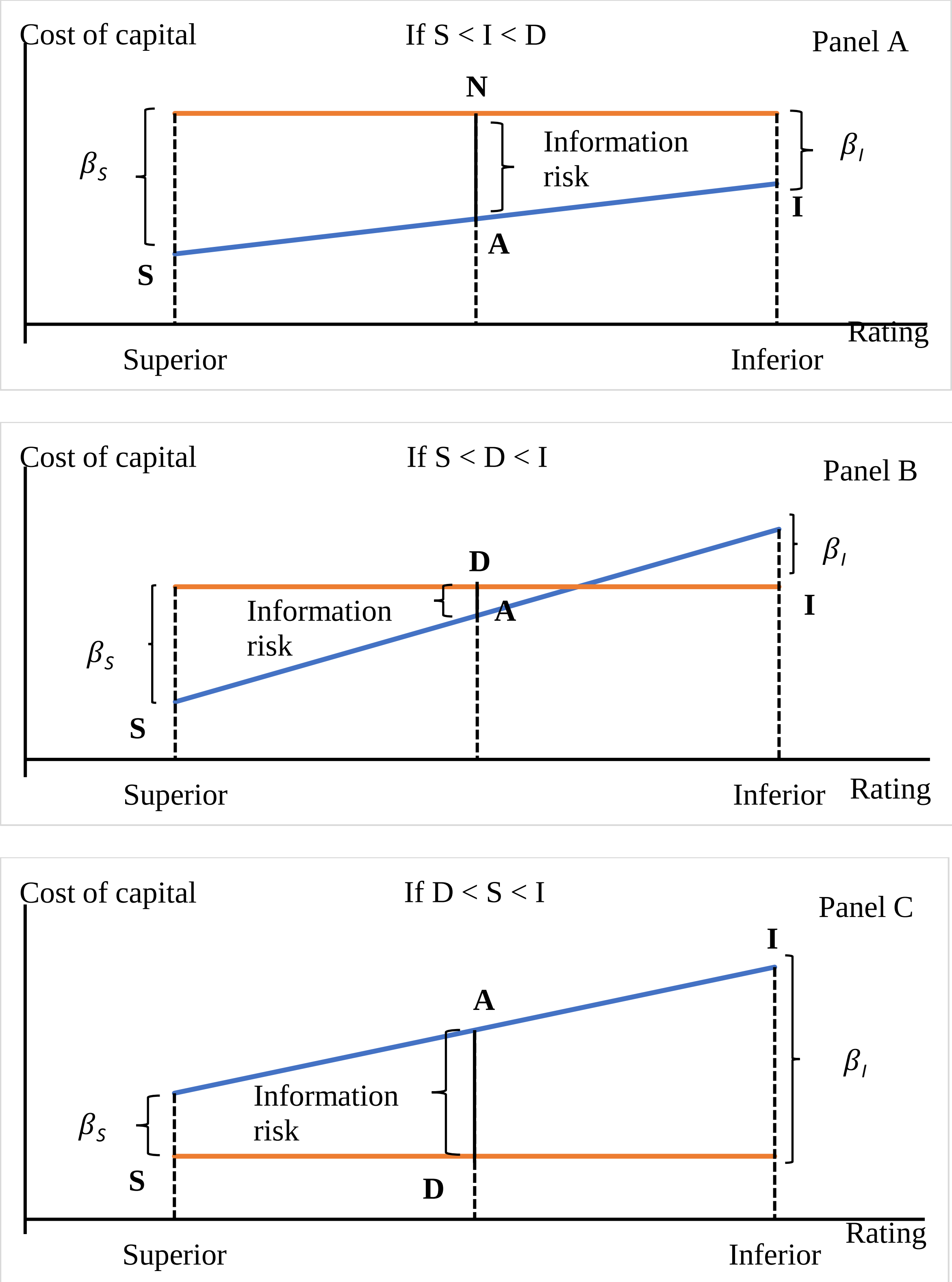

Figure 3.D.1. Illustration of information risk, credit risk and cost of capital

I is the estimated cost of equity capital on split rated firms if both CRAs had assigned the same inferior rating level. *S* is the estimated cost of equity capital on split rated firms if both CRAs had assigned the same superior rating level. *A* is the average of *I* and *S*. *D* is the actual cost of equity capital of the split rated firms. The difference between *D* and *A* is the information risk arising from split ratings.

Table 3.D.1 reports the results of the two regression models, Superior Rating Model and Inferior Rating Model. In the superior rating model, the coefficient for *ASPLIT_DUM* (β_S) is 0.442 and marginally significant, suggesting that an inferior rating significantly increases the cost of equity capital of split-rated firms. The cost of equity capital for split-rated firms is about 44 basis points higher when compared to the estimated cost of equity capital for these firms if both CRAs had assigned the same superior ratings level. In the inferior rating model, the coefficient for *ASPLIT* (β_I) is 0.433 and significant, suggesting that even with a superior rating, split ratings still significantly increase the cost of equity capital of split-rated firms. Because the coefficients for *ASPLIT_DUM* in both the superior model and the inferior model are positive and significant, the actual cost of equity capital of split-rated firms is above the estimated level for these firms if both CRAs had assigned the same superior or inferior ratings level (as illustrated in Panel A of Figure 3.D.1). The cost of equity capital for split rated firms is typically 43.7 basis points (i.e., (0.442 + 0.433)/2 = 0.437) higher when compared to the estimated cost of equity capital for these firms if both CRAs had assigned the same inferior ratings level. This is consistent with the baseline results, suggesting that equity investors do require a higher premium to compensate for the information risk arising from split ratings.

Table 3.D.1. Superior rating model, inferior rating model and the cost of equity capital

Variables	Expected sign	Superior Rating Model (I)	Inferior Rating Model (II)
ASPLIT_DUM	+	0.442***	0.433**
		(2.74)	(2.50)
ROE	-	-0.258**	-0.251**
		(-2.14)	(-2.09)
D2A	+	2.015**	1.914*
		(2.04)	(1.80)
BM	-	-0.066	-0.059
		(-0.33)	(-0.30)
BETA	+	-0.096	-0.085
		(-0.47)	(-0.40)
STDNI	+	65.602***	66.360***
		(5.63)	(5.74)
IDIO	+	0.072*	0.071*
		(1.94)	(1.77)
Constant		-7.218***	-7.380***
		(-4.78)	(-4.87)
Rating Level		Yes	Yes
Year*Industry		Yes	Yes
Observations		5,986	5,986
Adjusted R-squared		0.076	0.072

Table 3.D.1. reports the results of Eq. (3.D.1) and Eq. (3.D.2) using OLS estimation. The dependent variable is the cost of equity capital in percentage. *ASPLIT* is the absolute annual split ratings. *ASPLIT_DUM* is a dummy variable which equals to 1 if a firm is split rated (*ASPLIT* > 0) and 0 otherwise. The control variables are return on equity (*ROE*), financial leverage ratio (*D2A*), book-to-market ratio (*BM*), systematic risk (*BETA*), earnings volatility (*STDNI*) and idiosyncratic risk (*IDIO*). See Table 3.2 for more detailed definitions. In the Superior (Inferior) Rating Model, the superior (inferior) rating of split rated firms are used to construct the rating dummy variables. Year*Industry interactions are included in the regressions. Values in parentheses are robust t-statistics. Standard errors are clustered by companies. ***, **, and * refer to significant coefficients at the 1%, 5%, 10% levels, respectively.

Chapter 4: Split ratings and debt maturity

4.1 Introduction

Debt maturity structure plays an important role in firms' financial policies. Asymmetric information theory suggests that the structure of debt maturity involves a trade-off between the potential benefit of favourable news in the future and the cost of refinancing/rollover risk (Flannery, 1986; Diamond, 1991). Firms' choice of debt maturity relies on the nature of its information, that is, firms with favourable private information prefer short-term debt and firms with unfavourable private information prefer long-term debt (Goyal and Wang, 2013). The risk of being unable to roll over maturing short-term debt, especially when the refinancing coincides with a deterioration of the firm's credit quality or adverse economic shocks, gives firms an incentive to rely on long-term debt (Diamond, 1991; Guedes and Opler, 1996; Badoer and James, 2016). For example, the collapse of Bear Stearns and Lehman Brothers during the U.S. financial crisis was partly due to their overreliance on short-term debt such that falling collateral values made them unable to refinance their maturing debt (Gopalan et al., 2014). Thus, recent theoretical and empirical literature considers rollover risk as additional credit risk for firms (He and Xiong, 2012a; Gopalan et al., 2014; Morris and Shin, 2016). The aim of this chapter is to examine the relationship between firms' debt maturity choice and credit rating agencies' (CRAs) disagreement about firms' creditworthiness.

Credit ratings reveal private information about firms' creditworthiness to potential debt investors and many investors rely on CRAs to assess credit risk (Cornaggia et al., 2018). It is well documented that credit ratings have a significant effect on firms' policies such as capital structure (Faulkender and Peterson, 2006; Kisgen, 2006; 2009), debt structure/different tiers of debt (Rauh and Sufi, 2010; Bedendo and Siming, 2018), and investment (Harford and Uysal, 2014; Karampatsas et al., 2014). Both theoretical and empirical literature supports a view that credit ratings are a key determinant of debt maturity structure. Diamond's (1991) model of debt maturity choice suggests that high-rated and low-rated firms borrow short-term debt while middle-rated firms are more likely to issue long-term debt. Empirical evidence from Johnson (2003) and Custódio et al. (2013) reveals that rated firms have longer debt maturity than their unrated peers.

In the United States, most corporate bonds are rated by the two major CRAs, namely Moody's and Standard & Poor's (S&P). Nevertheless, Moody's and S&P ratings very frequently differ from each other, resulting in split ratings (Livingston et al., 2010). Previous credit rating literature finds that ratings from Moody's and S&P are important for both investors and corporate insiders such that when split ratings occur, split rated bonds have higher yields than non-split rated bonds (Livingston et al., 2010; Livingston and Zhou, 2010). Furthermore, split rated bonds are much more likely to receive further rating actions from CRAs in the near future (Livingston et al., 2008). Split ratings are thus expected to have some effect on firms' debt maturity choice. This has not previously been explored in the literature, hence this chapter will explore this void.

Theoretically, split ratings may encourage firms to borrow at the short end of the spectrum in order to avoid the likely higher long-term borrowing cost arising from the CRAs' disagreement, as mentioned above. Because split ratings indicate a greater information asymmetry problem to outside investors, firms may opt for short-term debt to signal their financial strength (Diamond, 1991) or to reduce the information asymmetry (Flannery, 1986).[33] Alternatively, it can be argued that refinancing risk leads split rated firms to rely more on long-term debt than their non-split rated peers. The threat of further rating changes (especially rating downgrades), and the associated financing risk, may outweigh the beneficial effect of revealing favourable private information which arises in issuing short-term debt (Badoer and James, 2016). Both lines of argument have their merits and therefore it is an interesting empirical question on firms' debt maturity choices in the presence of split ratings.

In order to answer this research question, this Chapter uses the annual average of daily differences at rating/outlook/watch status to generate the key independent variable, split ratings. By doing so, this chapter is thereby able to capture not only the magnitude but also the persistence of the split. This, in turn, provides us with a promising setup for testing the impact of split ratings on firms' behaviour for two reasons. First, short-lived splits are much less important than persistent splits; indeed, CRAs could disagree with each other for a short period of time due to small differences in the timing of rating processes or rating actions. Second, the larger the gap between the two CRAs, the greater uncertainty exists across CRAs about borrowers' creditworthiness and this uncertainty could lead to more severe rating actions from CRAs in the future.

The sample covers 2002 – 2015 and includes all listed U.S. firms with long-term credit ratings from both S&P and Moody's. Debt maturity is defined as the ratio of long-term debt over total debt and is calculated using multiple approaches used in the prior literature

[33] Greater information asymmetry increases the cost of debt and the frequency of credit events (e.g. defaults), and hence gives firms incentives to borrow on a short-term basis (Derrien et al., 2016).

(Custódio et al., 2013; Keefe and Yaghoubi, 2016). The results show that firms with split ratings have more long-term debt than firms with non-split ratings. A one-notch split rating is associated with 2.1% (2.7%) higher proportion of long-term debt maturing in more than 3 (5) years. The finding suggests that firms are more concerned with future rating migrations and the refinancing/rollover risk associated with those changes than with any potential increase in the cost of debt arising from a current split rating. This is consistent with Goyal and Wang's (2013) finding that firms experience a negative unexpected rating change subsequent to issuing long-term debt and that firms rely on longer-term debt due to their anticipation of such unfavourable changes. The results are also in-line with the results in Gopalan et al. (2014) showing that firms with an increase in the amount of long-term debt due within one year (which is defined as short-term debt in this thesis) are downgraded more severely by CRAs. Therefore, split rated firms would benefit from increasing their proportion of long-term debt over total debt to avoid this potential future deterioration in their credit standing.

The study's main contributions are as follows. It is unique in examining the impact of split ratings on debt maturity structure. Previous studies connecting credit ratings and debt maturity examine the effects of only one CRA (either Moody's or S&P). In providing evidence that ratings from both CRAs matter, the study reinforces the ongoing relevance of credit ratings in the sphere of corporate debt, alongside Karampatsas et al. (2014), Harford and Uysal (2014), Bedendo and Siming (2018), Driss et al. (2019), and others. This chapter also highlights split ratings as a neglected issue in recent research on firms' debt maturity decisions.[34]

At the time of writing, U.S. firms have issued a historically large amount of debt in recent years; hence this chapter provides timely evidence on some potential repercussions. The remainder of this chapter is organised as follows: Section 4.2 reviews the existing literature on debt structure and credit ratings. Section 4.3 develops the hypothesis, and the research design is discussed in Section 4.4. Section 4.5 discusses the data sample, Section 4.6 presents the empirical results, and Section 4.7 concludes.

[34] Huang et al. (2016) and Dang and Phan (2016) study the link between chief executive officer (CEO) characteristics and corporate debt maturity. Keefe and Yaghoubi (2016) study the association of firm cash flow volatilities with corporate capital structure and maturity choices. González (2015) studies the influence of the financial crisis on corporate debt maturity.

4.2 Literature review

Chapter 2 provides a detail discussion of the previous literature on systematic differences between CRAs' ratings and the impact on firms' debt issuance. Section 3.2 of Chapter 3 discusses the existing literature regarding rating dispersion and the cost of capital. In this section, the literature on debt structure and credit ratings as well as the gaps within the literature are examined.

The relationship between credit ratings and debt maturity structure has received attention in both theoretical and empirical literature. Flannery's (1986) asymmetric information model suggests that firms' debt maturity reflects the choice between the beneficial effect of expecting future news to be favourable and rollover risk. Thus, the implication of the asymmetric information model is that firms with positive private information about their credit quality will benefit from refinancing on favourable terms by issuing short-term debt because the market underestimates the firms' credit quality and vice versa. Diamond (1991) proposes a model of debt maturity choice where firms with low- and high-credit quality typically borrow short-term. Diamond's (1991) theory states that firms have to balance between the preference for short-term debt and the increase in liquidity risk. High-credit quality firms borrow short-term to signal that they have strong finance and are not concerned about the possibility of a liquidity shock. Moreover, financing with short-term debt allows them to refinance when the market is favourable. On the other hand, middle- and low-credit quality firms prefer borrowing debt at the long end of the spectrum. The lowest credit quality firms do not have any other options but to borrow short-term. Rauh and Sufi (2010) suggest that high-credit quality firms focus on two tiers of capital: senior unsecured debt and equity, while lower-credit-quality firms use secured, senior unsecured and subordinated issues. This is consistent with Diamond's (1991) argument that the relationship between debt maturity and credit ratings is non-monotonic.

The empirical literature has tested the implications of asymmetric information models in this context and shed light on the relationship between credit ratings and firms' debt maturity decisions. Johnson (2003) shows that ratings have a negative correlation with short-term debt maturity, suggesting that it is easier for rated firms to issue long-term debt than it is for firms with restricted access to the credit market. Consistent with this, Custódio et al. (2013) find that rated firms have longer debt maturity than unrated firms. They further argue that unrated firms have greater information asymmetry than rated firms because CRAs bring more private information to the public domain. Consequently, firms with less information asymmetry are more likely to use long-term debt. Goyal and Wang (2013) find that short-term debt issuers experience improvement in their credit ratings and long-term debt issuers experience deterioration in their credit ratings, confirming the implications of asymmetric information models.

Other studies have shown evidence that debt maturity decisions depend on different credit rating levels (Barclay and Smith, 1995; Guedes and Opler, 1996; Badoer and James, 2016; Driss et al., 2019). Barclay and Smith (1995) find that bond rating levels have a negative relationship with debt maturity, meaning that lower-rated firms issue more long-term debt than higher-rated ones. Guedes and Opler (1996) also show that credit rating levels affect whether firms borrow long-term/short-term. Their findings suggest that large firms with investment-grade credit ratings are more likely to borrow at the short end and the long end of the maturity spectrum, while firms with speculative-grade ratings tend to borrow in the middle of the maturity spectrum. The reason for such differences is attributed to firms with lower ratings being more likely to issue long-term debt in order to avoid any risk of inefficient liquidation. Consistent with Guedes and Opler (1996), Badoer and James (2016) state that the majority of longer-term debt (maturing in greater than 20 years) is issued by investment-grade firms, suggesting that credit rating levels affect firms' preferred debt maturity. All of these decisions are subject to the market's willingness to fund the firm's preferred structure. In addition to credit rating levels, CRAs' signals of future rating changes (outlook/watch status) also have a significant effect on firms' financial policies. Driss et al. (2019) find that firms receiving a credit watch warning which results in no rating change increase their long-term debt financing and investment activities.

There is also evidence that the close-to-mature debt has a potential effect on firms' future credit ratings. Gopalan et al. (2014) show that firms with a high level of long-term debt maturing within one year are more likely to receive a rating downgrade during the next year. They attribute this to the fact that short-term debt (debt maturing within 3 years) exposes firms to the risk of being unable to refinance their maturing debt, especially when there is a deterioration in firm fundamentals or market conditions. Their findings imply that firms with increased exposure to refinancing risk or rollover risk are more likely to be downgraded by CRAs and to have higher bond yield spreads.

Despite the above research on credit ratings and debt maturity, most of this literature has investigated credit rating effects from only one CRA. Debt maturity studies tend to use rating data from S&P (Barclay and Smith, 1995; Guedes and Opler, 1996; Custódio et al., 2013; Gopalan et al., 2014; Dang and Phan, 2016; Huang et al., 2016; Keefe and Yaghoubi, 2016), with fewer using Moody's ratings (Rauh and Sufi, 2010; Driss et al., 2019). Since Moody's and S&P ratings differ more often than they agree, credit rating literature has found that the market perceives ratings from those two CRAs differently (Livingston et al., 2010). Using a sample of 6,652 newly issued, split rated, U.S. corporate bonds from 1983 to 2008, Livingston et al. (2010) find that split rated bonds have a higher cost of debt than non-split rated. Split rated firms with superior S&P ratings have a higher cost of debt than split rated firms with superior Moody's ratings (thereby Moody's is designated as being more conservative than S&P).

To sum up, while credit rating effects are one of the most important factors for firms' managers to consider when making decisions on debt maturity structure, the effect of the differences in opinion between CRAs has not yet been investigated. In addition, no evidence exists on the potential link between the superior ratings from one particular CRA and debt maturity structure. Since split ratings and rating conservativeness have a significant effect on the supply side of the debt market, one might expect the disagreement between two CRAs to also have a significant impact on firms' future behaviour regarding debt maturity structure. Further, the prior literature also shows that information asymmetry is an important determinant of both capital structure and debt maturity decisions (Goyal and Wang, 2013; Petacchi, 2015). Because split ratings are a signal of information opacity, this could reinforce any impact of split ratings on firms' debt maturity choices.

4.3 Hypothesis development

This section explains the hypotheses to examine the relationship between split rating and corporate debt maturity structure. The first hypothesis is related to the first research question:

H_{1A}: *Split ratings have a significant effect on debt maturity structure.*

The null hypothesis is that split ratings do not influence a firm's decision-making on debt maturity. If this hypothesis is rejected, firms' managers must recognise the potential impact of split ratings and adjust the debt maturity structure. There are two contrasting viewpoints under which split ratings can affect firms' debt maturity structure.

The first viewpoint is firms with split ratings using more short-term debt. According to the signalling theory, firms with greater information asymmetries should issue more short-term debt because their long-term debt is more likely to be mispriced (Flannery, 1986). Split rated firms are expected to borrow more short-term debt to signal their financial strength and reduce the information asymmetry problem, since split ratings convey uncertainty and ambiguity surrounding firms' creditworthiness. Using short-term debt also helps firms to reduce the potential conflict of interest between firms' shareholders and bondholders (Barnea et al., 1980). Flannery (1986) further argues that firms in industries with greater information asymmetry tend to issue more short-term debt to signal their current debt portfolio's credit quality. Firms with shorter debt maturity are subject to more frequent monitoring from outsiders (via refinancing and renegotiation); thus, they experience less information asymmetry and agency problems (Datta et al., 2005). Furthermore, empirical evidence suggests that split ratings increase the cost of long-term debt (Livingston et al., 2010; Livingston and Zhou, 2010), and since short-term borrowing costs are relatively insensitive to changes in firms' default risk (Guedes and Opler, 1996), one might expect that firms with split ratings are more likely to opt for short-term debt to avoid higher long-term borrowing cost.

The second viewpoint is firms with split ratings using more long-term debt. According to information asymmetry models, firms with unfavourable private information are more likely to issue debt at the long end of the maturity spectrum. Firms which use short-term debt more often are exposed to excessive liquidity risk, and hence, are at risk of being unable to refinance in the event of a credit rating downgrade. Gopalan et al. (2014) suggest that firms with greater exposure to rollover risk are more likely to receive rating downgrades and have higher bond yield spreads. In addition, split rated firms have a higher probability of rating changes in the near term than do non-split rated firms (Livingston et al., 2008). Given the potential for unfavourable rating changes in the future, firms with split ratings may prefer to use more long-term debt to avoid the refinancing risk, further rating deteriorations, and more costly borrowing.

The second hypothesis addresses whether firms' managers differentiate between Moody's and S&P ratings when making debt maturity decisions, as follows:

H_{2A}: Superior ratings from Moody's have a different impact on firms' debt maturity structure than superior ratings from S&P.

The null hypothesis is that Moody's and S&P ratings are not treated differently. The alternative hypothesis is that firms with superior ratings from one CRA act differently than firms with superior ratings from the other CRA. Livingston et al. (2010) investigate the impact of split ratings between Moody's and S&P on bond yields and find that firms with superior Moody's ratings have significantly lower bond yields than firms with superior S&P ratings. This implies that the cost of debt for firms with superior Moody's ratings differs from that for firms with superior S&P ratings. In a similar vein, this chapter investigates whether superior ratings from S&P have a different impact on debt maturity than superior ratings from Moody's. Using survey evidence, Baker and Mansi (2002) report that firms' managers consider S&P to be a more accurate CRA. If this holds, when firms are assigned superior Moody's ratings, they would be more concerned about the mispricing of their long-term debt and consequently issue more short-term debt than firms with superior S&P ratings. Another line of argument is that CRAs have become more conservative in rating firms' creditworthiness over time (Baghai et al., 2014). Also, there is some evidence that Moody's is generally a more conservative CRA in rating U.S. corporates (Livingston et al., 2010). In cases when S&P assigns higher ratings than Moody's, one might expect that S&P ratings will be downgraded to match Moody's ratings rather than vice versa. If this holds, firms with superior S&P ratings may issue more long-term debt in anticipation of future rating downgrades.

4.4 Research design

4.4.1 Split ratings and debt maturity

To examine the effect of split ratings on debt maturity structure (H_{1A}), the following fixed effects model is estimated:

$$DM_{i,t} = \beta_0 + \beta_1 ASPLIT_{i,t-1} + \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t-1} \qquad (4.1)$$
$$+ \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t}$$

$DM_{i,t}$ is the debt maturity ratio (*DM3* and *DM5* are defined in Section 4.4.2) for firm *i* in year *t*, defined as the proportion of firms' long-term debt that is due in more than 3 or 5 years over total debt (more details appear in Section 4.4.2). $ASPLIT_{i,t-1}$ is the absolute split rating between S&P and Moody's for firm *i* in year *t – 1*, defined in Section 4.4.3. Under H_{1A}, split ratings are either positively or negatively related to firms' reliance on long-term debt, which would imply $\beta_1 \neq 0$. $CONTROL_{i,j,t-1}$ consists of a set (*j* = 8) of characteristics for firm *i* in year *t – 1* defined in Table 4.1, including median industry debt maturity (*INDDM*), market-to-book assets ratio (*MTB*), tangibility (*TANG*), profits (*PROFIT*), firm age (*AGE*), research and development expenses (RD), equity issues (EI), and assets (*FS*) (more details appear in Section 4.4.4). $LEVEL_{i,k,t-1}$ is a set of 19 dummy variables representing the average rating level (*k*) of firm *i* at time *t – 1*. *YEAR×INDUSTRY* is the interaction term of year and industry dummy variables, which controls for time and industry fixed effects, whereby *l* represents year (13 years) and *m* represents 8 industries based on 1-digit SIC code. Table 4.1 defines all variables and indicates their data sources. The standard errors are clustered at the firm level.

Following previous related literature (e.g. Brav, 2009; Ben-Nasr et al., 2015; González, 2015; Belkhir et al., 2016), Eq. (4.1) is estimated using OLS. Nevertheless, Eq. (4.1) is also estimated using the Tobit and GLM approaches, which are applied in the corporate finance literature to deal with ratio dependent variables (e.g. Barclay and Smith, 1995). See Section 4.4.5 for more details on these estimation techniques.

To examine the effect of superior Moody's versus superior S&P ratings (H_{2A}), the following fixed effects model is estimated:

$$\begin{aligned} DM_{i,t} &= \beta_0 + \beta_1 SUP\_MOODY_{i,t-1} + \beta_2 SUP\_S\&P_{i,t-1} \\ &+ \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t-1} \\ &+ \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \end{aligned} \tag{4.2}$$

$SUP\_MOODY_{i,t-1}$ ($SUP\_S\&P_{i,t-1}$) is a dummy variable, which is equal to 1 if Moody's (S&P) rating is higher than S&P (Moody's) rating for firm *i* in year *t – 1*. $DM_{i,t}$, *CONTROL*, *LEVEL* and *YEAR×INDUSTRY* are defined as in Eq. (4.1). Eq. (4.2) is also estimated using OLS, Tobit and GLM.

4.4.2 Debt maturity

Following previous literature (Barclay and Smith, 1995; Barclay et al., 2003; Custódio et al., 2013; Dang and Phan, 2016)[35], the long-term debt that matures in more than three years is considered, with the dependent variable labelled as *DM3*. Under this definition, corporate debt maturity is the proportion of firms' long-term debt that is due in more than three years divided by long-term debt and debt in current liabilities. Thus, *DM3* allows debt maturity to be separated from the leverage decision (Barclay and Smith, 1995).

$$DM3 = \frac{dltt - dd2 - dd3}{dltt + dlc} \tag{4.3}$$

[35] Dang and Phan (2016) define debt maturity as the ratio of debt due in less than three years to total debt.

DM3 is the ratio of long-term debt (*dltt*) minus debt maturing in the second and third year to total debt. $dd2$ and $dd3$ are the total amounts of long-term debt due within the second and third year from the balance sheet date.

DM5 is also used as another measure of debt maturity, whereby the debt maturity structure is the ratio of firm's total debt maturing in more than five years divided by the total debt (Custódio et al., 2013; Dang and Phan, 2016).

$$DM5 = \frac{dltt - dd2 - dd3 - dd4 - dd5}{dltt + dlc} \tag{4.4}$$

DM5 is the ratio of the long-term debt minus debt maturing in the second, third, fourth and fifth years to total debt. $dd4$, and $dd5$ are the total amount of long-term debt due within the fourth and fifth year from the balance sheet date.

4.4.3 Split ratings

ASPLIT is the variable that captures the disagreement between Moody's and S&P. Similar to Chapter 3 (Section 3.4.4), the 58-point comprehensive credit rating (CCR) scale (Sy, 2004), which takes into account rating level, outlook and watch status, is used. Credit ratings are transformed as follows: Aaa/AAA = 58, Aa1/AA+ = 55, …, Caa3/CCC– = 4, Ca/CC/C/SD = 1, then add + 1 (– 1) for positive (negative) outlook and add + 2 (– 2) for positive (negative) credit watch. Using the CCR, this study calculates split ratings as the average of absolute daily differences between Moody's and S&P ratings (the direction of the split used is (Moody's – S&P)) over each firms' fiscal year. Split ratings are then rounded to the nearest integer to remove the effect of short-lived splits. More discussion about short-lived or temporary split is available in Chapter 3 (Section 3.4.4). Split ratings of more than 4-CCR units are grouped into one category because these large splits are uncommon (see Table 4.4).[36]

To separate the superior Moody's ratings and superior S&P ratings, a second variable, *SPLIT* is calculated as the average of daily differences between Moody's and S&P (without using absolute values). By doing so, the positive and negative cases of the daily split can offset each other, and the direction of average rating split is preserved. This allows the test to reveal the impact of a more conservative CRA or a more generous CRA on debt maturity structure. *SPLIT* is also rounded to the nearest integer to remove the effect of temporary splits. Eq. (4.2) is estimated using two dummy variables, *SUP_MOODY* and *SUP_S&P*. *SUP_MOODY*

[36] Additional robustness test without this specification (grouping split ratings more than 4-CCR) shows similar results to those of the baseline model (See Table 4.B.8 in Appendix 4.B).

(*SUP_S&P*) is equal to 1 if *SPLIT* is positive (negative), i.e. Moody's (S&P) ratings are superior to S&P (Moody's) ratings in year *t*.[37]

4.4.4 Control variables

A set of control variables is also included. In their study of factors in capital structure decisions, Frank and Goyal (2009) report six variables for explaining firms' leverage: median industry leverage (*INDFL*), market-to-book asset value ratio (*MTB*), tangibility (*TANG*), profits (*PROFIT*), assets (*FS*), and expected inflation (*INFLA*). Hence, in this study, five of these factors, except *INFLA*, are implemented to explain firms' debt ratios. There are two reasons for excluding *INFLA*. First, Frank and Goyal (2009) themselves state that expected inflation is the least reliable factor among the six factors mentioned above. Since expected inflation is the macro-economic factor, its number of observations is far less than the others, and consequently, according to Frank and Goyal (2009), expected inflation does not possess the same level of confidence to perform similarly out of sample as other factors. Second, in the main regression model, macro-economic conditions are controlled by the interacting fixed effects (Year*Industry dummies). Previous literature (e.g., Jiménez et al., 2012; Klusak et al., 2017) states that there is a doubtful need for any other macro variable when the interacting fixed effects are used.[38] In addition to the five aforementioned "core" factors, three additional explanatory variables (ratio of research & development expenses to sales (*R&D*), firm age (*AGE*) and equity issues (*EI*)) are included to further diminish any effect of omitted variable bias (Custódio et al., 2013; Dang and Phan, 2016; Díaz-Díaz et al., 2016). Furthermore, four additional variables, the ratio of cash and marketable securities to the total assets (*CASH*), idiosyncratic volatility (*IDIO*), leverage (*D2A*) and the ratio of tax expenditure to total assets (*TAXES*), are added for the propensity score matching. All variable definitions and constructions appear in Table 4.1.

[37] The terminology of 'superior' and 'inferior' is based on that used in in prior split rating literature (e.g. Livingston et al., 2010).
[38] An additional investigation shows that the INFLA variable and interacting fixed effects are highly correlated. Thus, dropping INFLA is appropriate to address this issue and to avoid any multicollinearity.

4.4.5 Research methodology

4.4.5.1 Limited dependent variable issue

The challenge with using ratios as the dependent variable is that the proportions are only observed on the closed interval [0,1] and there is not any observation outside this certain range. In this section, different approaches used in prior literature to tackle the limited dependent variable issue are presented.

OLS model.

The OLS regression is a common practice of many researchers, when there is a limited dependent variable (e.g., Bharath et al., 2009; Brav, 2009; Frank and Goyal, 2009; Gropp and Heider, 2010; Margaritis and Psillaki, 2010; Belkhir et al., 2016). The OLS regression model is presented as:

$$y_i = \beta \boldsymbol{X_i'} + \varepsilon_i \tag{4.5}$$

where y_i is the dependent variable of i, $\boldsymbol{X_i'}$ is a vector of exogenous variable for i, and ε_i is the error term. There are three assumptions regarding the use of OLS, as explained by Kieschnick and McCullogh (2003):

- The observed proportions are assumed to be observed in an open interval (0,1), which mean most of the data points are in between the bounded range and no mass point exists at either end of the boundary, the value zero and one. Consequently, these assumptions allow the proportions to be modelled using a continuous distribution.
- The conditional distribution of the regression model is normally distributed $f(y|\boldsymbol{X}) \sim N(\mu, \sigma^2)$, where $\mu = E(y|\boldsymbol{X})$**.** This assumption of the conditional normal distribution is to ensure the Normality Assumption of the linear regression model.
- $E(y|\boldsymbol{X}) = \beta \boldsymbol{X}$ or $E(\varepsilon|\, \boldsymbol{X}) = 0$, that means that the conditional expectation function is linear.

The normal conditional distribution assumption also implies that the proportions are normally distributed. Researchers justify this assumption by stating the proportions' histograms have superimposed a normal distribution (see, for example, Kieschnick and McCullogh, 2003, p. 194). The third assumption is to tests for the absence of heteroscedasticity in the error terms. With these three assumptions, OLS regression can be used to estimate specifications with a limited dependent variable (in this case, ratio dependent variable) without breaking any of the six assumptions for the linear regression model.

However, even with the three assumptions that need to be made, there are many drawbacks to this approach. First, the distribution of ratio dependent variable (in this case, debt maturity ratio) can be discrete distribution or mixed discrete-continuous distribution and ratio variable are not defined over real domain $\Re$, over which normal distribution is defined (Kieschnick and McCullough, 2003). Consequently, limited dependent variables are clearly not normally distributed and this violates the normality assumption. Second, since the observed variables lie within a closed interval, the conditional expectation function must be non-linear. That means the error term is heteroskedastic and this is clearly a violation of the Normality assumption. As a result, using OLS regression with a proportion dependent variable is not the most efficient and unbiased estimator since the coefficients *t* and *F* statistics may not follow *t* and *F* distributions. Thus, two different approaches (Generalized linear model and Tobit model) are proposed by prior literature (Barclay and Smith, 1995; Papke and Wooldridge, 1996; Kieschnick and McCullough, 2003) to overcome these disadvantages of the OLS regression in this setting.

Tobit model

One assumption that researchers make for the use of OLS regression is that the proportions are observed in an open interval (0,1). However, for many data sets (see, for example, Tobin, 1958; Melenberg and van Soest, 1996; Rezitis, 2006; Hsiao et al., 2010; Barth et al., 2013), zero and one values account for a significant fraction of the total observations. Consequently, these data can only be modelled using a mixed discrete-continuous distribution. Hence, the argument against conventional regression method (OLS) is that it “fails to take into account the qualitative difference between limit (zero) observations and nonlimited (continuous) observation” (Greene, 2003).

One approach of handling the discrete-continuous problem is to treat the proportion variable as a censored variable. The regression model to deal with this type of dependent variable is the censored regression model or Tobit model and it is used frequently in corporate finance literature (Rezitis, 2006; Hsiao et al., 2010; Barth et al., 2013) In this model, the data points below zero and above one are considered to be censored and unobservable. In addition, the dependent variable is assumed to be normally distributed but only observed within the interval of zero and one. The error term is also assumed to be a continuous random variable with mean 0 and variance σ^2. This assumption is the key to successful and unbiased estimations of the Tobit model. The advantage of the Tobit model is that it considers the mixed discrete-continuous distributed attribution of the proportions. In this study, since there are three conditional mean functions to consider, the two-limit Tobit model (Barclay and Smith, 1995; Long, 1997) is implemented.

$$E(DM^*_{i,t}|SPLIT_{i,t-1}, X_{i,,t-1}) = X_{i,,t-1}\beta + u_i$$

$$DM_{i,t} = \begin{cases} 1, & DM^*_{i,t} \geq 1 \\ DM^*_{i,t}, & 0 < DM^*_{i,t} < 1 \\ 0, & DM^*_{i,t} \leq 0 \end{cases} \quad (4.6)$$

where:

$DM^*_{i,t}$ is the debt maturity ratio of firm i at time t.

$X_{i,t-1}$ is a vector of independent variables (see Section 4.4.3 and Section 4.4.4) of firm i at time $t - 1$.

β is a vector of coefficients.

u_i is an independently distributed error term, assumed to be normally distributed with zero mean and constant variance σ^2.

The likelihood function (Greene, 2003) is given by:

$$L = \prod_{I_i=2}\left[\mathrm{I} - \Phi\left(\frac{1 - X_{i,,t-1}\beta}{\sigma}\right)\right]\prod_{I_i=1}\left[\frac{\mathrm{I}}{\sigma}\phi\left(\frac{DM_{i,t} - X_{i,,t-1}\beta}{\sigma}\right)\right]\prod_{I_i=0}\left[\Phi\left(\frac{0 - X_{i,,t-1}\beta}{\sigma}\right)\right] \quad (4.7)$$

where $I_i = 2$ if firm *i* has a debt ratio above 1, $I_i = \mathrm{I}$ if firm *i* has a debt ratio between 0 and 1, and $I_i = 0$ if firm *i* has a debt ratio below 0. Maximization of this function provides an estimation of β and σ.

The marginal effects on the latent dependent variable, DM^*, are calculated as follows:

$$\frac{\partial E(DM^*)}{\partial X_k} = \beta_k \quad (4.8)$$

Eq. (4.8) shows how a one unit change in the independent variable leads to a change in the latent dependent variable.

The marginal effect on the expected value for DM for uncensored observations:

$$\frac{\partial E(DM|0 < DM < 1)}{\partial X_k} = \beta_k\left\{1 - \lambda(\alpha)\left[\frac{X_i\beta}{\sigma} + \lambda(\alpha)\right]\right\} \quad (4.9)$$

where $\lambda(\alpha)$is called the inverse Mills Ratio and calculated as $\lambda(\alpha)=\frac{\phi\left(\frac{X_i\beta}{\sigma}\right)}{\Phi\left(\frac{X_i\beta}{\sigma}\right)}$. Eq. (4.9) shows how a one unit change in the independent variable leads to the change in the uncensored dependent variable.

The marginal effect on the expected value of *DM*:

$$\frac{\partial E(DM)}{\partial X_k}=\beta_k\times\Phi\left(\frac{X_i\beta}{\sigma}\right) \tag{4.10}$$

A change in X_k affects the conditional mean $E(DM)$ and affects the probability that the observation $DM^*_{i,t}$ will fall in a certain part of the distribution. Wooldridge (2010) suggests reporting both the marginal effects on the expected value of *DM* and the expected value of *DM* for uncensored observation.

One drawback of the Tobit model is to assume that $DM^*_{i,t}$ is normally distributed but can only be observed within a certain range. This assumption means that the proportions outside the [0,1] range are censored. However, the proportional values outside the [0, 1] interval fail to be observed not because they are censored, but because these values are not definable outside the interval (Kieschnick and McCullough, 2003). For example, in the case of capital structure, the zero-leverage observation is the result of firms choosing not to issue debt and to rely solely on equity. It is not the result of having negative debt and substituting zero for leverage. Therefore, it would be inappropriate to apply the censored regression model to non-censored data. Furthermore, the Tobit model also makes the same assumption about the error distribution, which is that it is independent and identically distributed draws from a normal distribution (Kieschnick and McCullough, 2003), and as mentioned before, the error term in regression with the limited dependent variable is likely to be heteroskedastic. Hence, the Tobit model estimators with heteroskedastic errors are severely biased. Overall, using the Tobit regression model for proportions as dependent variables does not produce the most efficient and unbiased estimations of the coefficients if the errors are not identically and normally distributed.

Generalized Linear Model (GLM)

In the OLS and Tobit approaches, one must presume some specific family of distributions for the dependent variable's conditional distribution. However, these assumptions are not always appropriate and thus, using these approaches do not necessarily yield the most efficient and unbiased results. In order to overcome this limitation, Papke and Wooldridge (1996) suggest a GLM model using the quasi-likelihood approach to deal with the use of proportions as a dependent variable. The foremost difference between GLM and the previous two approaches is that GLM only specifies the first and second moments of the conditional distribution rather than the full distribution (Kieschnick and McCullough, 2003). As a result, in GLM, the dependent variable does not need to be normally distributed and the error term only needs to be independent but does not need to follow a normal distribution. With this relaxation of the conditional distribution, the GLM fits better with the characteristics of proportions as a dependent variable. Thus, in this study, a GLM with a logit link function and quasi-likelihood function are used (Papke and Wooldridge, 1996; Kieschnick and McCullough, 2003; Keefe and Yahgoubi, 2016).

$$E(DM_{i,t}|X_{i,,t-1}) = G(\beta_0 + \beta_1 X_{i,t-1} + \ \varepsilon_{i,t}) \tag{4.11}$$

where:

G(.) is the logistic link function

DM is the debt maturity ratio.

$X_{i,t-1}$ is a matrix of lagged explanatory variables (including the main independent variable, control variables, LEVEL and INDUSTRY*YEAR interactions, see Sections 4.4.3 and 4.4.4).

As aforementioned, the GLM regression model uses a logistic link function *G(.)* which satisfies 0 < *G(z)* < 1 for all $z \in \mathbb{R}$. The link function ensures the predicted value of the dependent variable lies in the interval (0,1). The logistic link function which is a cumulative distribution function (cdf) is presented as follows:

$$G(\beta X_{i,t-1}) \equiv \frac{\exp\,(\beta X_{i,t-1})}{1 + \exp\,(\beta X_{i,t-1})} \tag{4.12}$$

The link function, in this case, allows the magnitude of the variable to be a function of its predicted value. Ultimately, the link function is to ensure that the predicted value of the dependent variable is well defined upon the interval [0,1] (Kapke and Woolridge, 1996).

Although, under Eq. (4.11), non-linear least squares (NLS) could consistently estimate the parameters β, the presence of heteroscedasticity, as $Var(RATIO_{i,t}|X_{i,,t-1})$ is unlikely to be constant, makes NLS become less efficient to estimate β. Thus, Kapke and Woolridge (1996) introduce a quasi-likelihood method. To estimate Eq. (4.11), the procedure is a quasi-likelihood method with the Bernoulli log-likelihood function:

$$l_i(\boldsymbol{b}) = RATIO_{i,t} \ln\left[G(X_{i,t-1}\boldsymbol{b})\right] + \left(1 - RATIO_{i,t}\right) \ln\left[1 - G(X_{i,t-1}\boldsymbol{b})\right] \tag{4.13}$$

Eq. (4.11) are well defined for 0 < *G(.)* < 1. The quasi-maximum likelihood estimators (QMLE) of β are obtained consistently from maximizing the equation:

$$\max_{b} \sum_{i=1}^{N} l_i(\boldsymbol{b}) \tag{4.14}$$

The most important characteristic of QMLE $\hat{\beta}$ is that it should be consistent and asymptotically normal regardless of the distribution of the dependent variable conditional on independent variables (Kapke and Woolridge, 1996). In other words, the dependent variable could be continuous, discrete or a mixed discrete-continuous variable, QMLE $\hat{\beta}$ is still efficient and effective.

Furthermore, the quasi-likelihood function, unlike the log-likelihood function, is not corresponding to any probability distribution and can estimate the conditional expectation of the dependent variable given the explanatory variables directly. Papke and Wooldridge (1996) show that this approach is more desired than any other approach as it does not need any special data adjustments regarding the extreme values of zero and one.

However, the GLM approach also has drawbacks. First, the quasi-maximum likelihood estimation assumes that

$$Var(DM_{i,t}|X_{i,,t-1}) = \sigma^2 G(\beta_0 + \beta_1 X_{i,t-1} + \varepsilon_{i,t})\left[1 - G(\beta_0 + \beta_1 X_{i,t-1} + \varepsilon_{i,t})\right] \quad \text{for some } \sigma^2 > 0 \tag{4.15}$$

Eq. (4.15) is frequently invalid because the group known size (n_i) is unlikely to be independent from the explanatory variables. Furthermore, the presence of unobserved group effects also leads Eq. (4.15) to fail. The second drawback of the GLM approach is that if Eq. (4.15) is not valid, a more complicated quasi-likelihood will be needed. However, with the more complicated quasi-likelihood, the original conditional link function Eq. (4.11) is no longer appropriate (Papke and Wooldridge, 1996). Hence, in order to proceed with the GLM method, one must accept the popular auxiliary assumption – Eq. (4.14). However, Papke and Wooldridge (1996) test the GLM regression with and without Eq. (4.14) and find the quasi-likelihood method is still fully robust. As a result, the quasi-likelihood method together with the GLM method is a robust and relatively efficient method of estimating fractional dependent variables.

Logit transformation.

As aforementioned, the problem with ratio dependent variables is that they are bounded between zero and one thresholds. One common practice in the literature on banks' nonperforming loans (NPLs) is to transform the dependent variable using logit function to create an unrestricted variable (e.g. Espinoza and Prasa, 2010; Jiménez et al, 2013). For instance:

$$LnDM3 = \ln\left(\frac{DM3}{1 - DM3}\right) \tag{4.16}$$

By doing so, the new transformed variable (*LnDM3*) is now unrestricted and can span over the real number interval from minus infinity to plus infinity and has a symmetrical distribution. This means that the proportional dependent variable is transformed to be a continuous variable and thus, it can be used in the OLS regression.

However, one drawback of the logit transformation is that when the proportional variable takes the value of 0 or 1, the logit function is unable to transform those observations. Thus, if the dependent variable has a large number of observations of 0 and 1, the estimation using a transformed variable could be biased because it fails to take into account those observations.

4.4.5.2 Endogeneity issues

Apart from the limited dependent variable problem, endogeneity is also another issue that needs to be considered in the research design. Endogeneity occurs when an independent variable correlates with the error term and thus, correct inferences or causal effects cannot be drawn from estimation (Wooldridge, 2010). In this study, endogeneity could arise in one of two ways. Firstly, simultaneity or reverse causality, where firms' choice of debt maturity could, in turn, have an impact on firms' probability of receiving split ratings from CRAs. Secondly, omitted variables, where there are unobserved additional variables that correlate with both dependent and explanatory variables. Thus, in this section, endogeneity is addressed by various techniques – including probit model and propensity score matching.

Probit model

In order to test whether there is simultaneity or reverse causality between split ratings and debt maturity as well as the relationship between split ratings and rating migrations, rating migrations are set to be the dependent variable. A dummy variable, *SPLIT_DUM,* which is equal to 1 if a firm's rating is split and 0, otherwise, is used. Since this dummy variable is a binary variable (0/1), the main dependent variable is discrete rather than continuous. Because of the discrete nature of the binary dependent variable, using OLS regression is not the best efficient and unbiased estimation.

The regression with a binary dependent variable is intended to measure the probability of that variable takes the value of 1 or 0. Thus, the cumulative probability distribution functions, which gives the probability between 0 and 1, are used to solve the binary problem. In this chapter, the probit regression model is:

$$SPLIT\_DUM_{i,t} = \beta_0 + \beta_1 DM_{i,t-1} + \gamma_j \sum_{j=1}^{7} EX_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t-1} + \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \tag{4.17}$$

where:

SPLIT_DUM is the split ratings dummy variable, which equals to 1 if firms are split rated (*ASPLIT* is above zero) and 0, otherwise.

$EX_{i,j,t-1}$ is the set of j (j = 7) explanatory variables for firm i at time $t-1$, including *FS*, *MTB*, *IDIO*, *CASH*, *TANG*, *BETA* and *RD* (see Table 4.1 for more details).

DM_{t-1} is the lagged debt maturity ($DM3_{t-1}$ and $DM5_{t-1}$) and the lagged first difference of debt maturity ($\Delta DM3_{t-1}$ and $\Delta DM5_{t-1}$).

The effect of a change in explanatory variables is calculated by taking the difference of the predicted probability of the initial value of explanatory variables and the predicted probability of the changed value of explanatory variables.

$$\frac{\partial E(DM_{i,t}|X_{i,,t-1})}{\partial X_{i,,t-1}} = \beta \times \Phi(\beta' X_{i,,t-1}) \tag{4.18}$$

In addition to *SPLIT_DUM*, a category variable (*ASPLIT1*), which is based on the split ratings variable (*ASPLIT*), is used as a dependent variable for Eq. (4.17). *ASPLIT1* has four different categories that correspond to 1-, 2-, 3- and more than 3-CCR unit split ratings of *ASPLIT*. Eq. (4.17) is then estimated using the ordered probit method.

Propensity score matching (PSM) method

Apart from the simultaneity issue, omitted variable bias is also a potential problem for this Chapter's research design. This would occur if debt maturity and split ratings might both correlate with some unobserved variables that the main model does not control for. To address this endogeneity issue, the propensity score matching approach is employed. Propensity score matching has become a more popular method to deal with endogeneity issues such as reverse causality, selection bias and omitted variables in the finance literature (e.g., Saretto and Tookes, 2013; Ben-Nasr et al., 2015; Khieu and Pyles, 2016; Almeida et al., 2017; Lu and Shi, 2018).[39] Since propensity score matching uses a nonparametric method to estimate causal effects, it is less likely to suffer from violating the assumption of exogeneity, which is the requirement for linear or logistic models to produce unbiased estimators. Thus, Li (2013) suggests using PSM as a robustness test to confirm the reliability of inferences from parametric models.

At first, the main sample is separated in two different groups: treatment group, which is a group of firms that receive split ratings from Moody's and S&P in a particular year, and control group, which is a group of firms that receive the same ratings from the two CRAs in a particular year. Then a probit model is estimated to calculate the probability of a unit being split rated ('treated' in the terminology of PSM).

$$\Phi^{-1}\big(e(\boldsymbol{X}_i)\big) = \boldsymbol{\beta}\mathbf{X}_i \tag{4.19}$$

where $\Phi()$ is the cumulative standard normal distributing function, $\boldsymbol{\beta}$ is the estimated coefficients vector of $\mathbf{X}_i$. $e(\boldsymbol{X}_i)$ is the propensity score of unit *i*. The characteristics $\mathbf{X}_i$ are firm size (*FS*), leverage (*D2A*), book value of cash over total assets (*CASH*), market-to-book value ratio (*MTB*), idiosyncratic risk (*IDIO*), taxes over total assets ratio (*TAXES*) as well as interaction terms of year and industry dummies and rating categories dummies (Gopalan et al., 2014; Almeida et al., 2017).[40]

In order to select a matched sample across the selected treatment and control groups, on the basis of propensity score, a matching method is needed. There are various matching methods, namely, nearest neighbour (NN) matching, caliper matching, radius matching, kernel matching and Mahalanobis metric matching (Pan and Bai, 2015). Each of these methods has its own pros and cons that are based on the trade-off between variance and bias (see Chapter 3, Section 3.4.6.4 and Table 3.3 for more details on matching methods). This chapter uses all aforementioned matching methods as robustness tests to rule out any bias arising from a given matching technique. The validity of the matching quality is assessed by using selection bias, standardized bias, joint significance and Pseudo-R^2 evaluation.

After a matching sample is created, the main regression, Eq. (4.1), is then re-estimated using the matched sample to control for unbalanced covariates. Previous literature finds that using that method could produce a robust estimate of the average treatment effect on the treated (ATT) (Schafer and Kang, 2008; Shadish et al., 2008).

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[39] More details about propensity score matching method are available in Chapter 3 (Section 3.4.6).

[40] Covariates used for calculating propensity score are partially different from those used for Eq. (4.1) because variables used to explain the probability of split ratings are distinct from those used to explain debt maturity.

4.5 Sample selection and data description

4.5.1 Sample selection

The data sample includes all listed U.S. corporations rated by the two major CRAs, Moody's and S&P, from 2003 to 2015.[41] Annual financial data (from 2002 because *ASPLIT* and *CONTROL* variables are lagged) are obtained from the Compustat database. Moody's and S&P rating data are obtained from Moody's website and Capital IQ database, respectively. Following Keefe and Yaghoubi (2016) and Frank and Goyal (2009), firms involved in a significant merger or acquisition (Compustat sales footnote code AB) are excluded from the sample.[42] The main sample includes both financial and utility firms (Standard Industrial Classification (SIC) codes 6000-6999 and 4900-4999, accordingly).[43] Furthermore, any firms with negative common equity, total assets or net sales or missing net sales, total liabilities or total assets are excluded from the sample. Following Keefe and Yaghoubi (2016), missing observations of the balance sheet and cash flow statement items: research and development expenses (*xrd*), *dd*, *dd1*, *dd2*, *dd3*, *dd4*, and *dd5* are set to be zero. However, Eq. (4.1) and Eq. (4.2) are re-estimated where this requirement of setting missing *xrd*, *dd*, *dd1*, *dd2*, *dd3*, *dd4*, and *dd5* equal to zero is lifted and results are robust.[44] All variables (except for *INDDM* and *ASPLIT*) are winsorized at 0.5% of both distribution tails to reduce the effect of outliers.[45] Table 4.2 reports the sampling process. The final sample contains 844 unique firms and 6,632 firm-year observations.

4.5.2 Descriptive statistics

Table 4.3 reports the summary statistics for all variables along with the pairwise correlation of explanatory variables. In Panel A of Table 4.3, the mean of *DM3* is 0.74, suggesting that, on average, rated firms use approximately 74% long-term debt. After

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[41] The rating outlook status of firms was made available on Moody's database in 2003, so this is chosen as the start date.

[42] Those firms experienced large changes in their sales, assets, liabilities, and debt structures. Thus, they are removed.

[43] Some prior studies in the debt maturity literature (Ben-Nasr et al., 2015; González, 2015; Dang and Phan, 2016; Keefe and Yaghoubi, 2016) exclude financial and utilities firms. However, Kisgen (2006) argues that credit ratings also affect these firms as well as industrial firms. Eq. (4.1) is re-estimated using a sample excluding financial, utility firms or both as robustness tests, and the results are consistent (See Appendix 4.B, Table 4.B.12 and Table 4.B.13)

[44] Results of these robustness tests appear in Appendix 4.B, Table 4.B.10 and Table 4.B.11

[45] Industry debt maturity (*INDDM*) is calculated as the median of all firms' debt maturity in the same industry (classified as 4-digit SIC codes). Thus, the measure is the same for all companies in a specific sector. The absolute rating splits (*ASPLIT*) variable is not winsorized because there are no particular outliers.

excluding debt due in the 4th year and 5th year, the proportion of long-term debt maturing in more than 5 years for half of the sample firms is above 57%. The mean log of firm size (*FS*) is 8.50, which is about US$ 4,910 million of total assets. Panel B of Table 4.3 presents the pairwise correlation matrix and shows no serious collinearity among independent variables. The split rating measure (*ASPLIT*) is negatively correlated with *FS*, *MTB*, *PROFIT*, *AGE*, and positively correlated with *EI*. These correlation coefficients are statistically significant at the 1% level. This is suggestive that firms with large or persistent split ratings are smaller, with fewer growth opportunities, less profitable, younger, and issue more equity.

Figure 4.1 shows the changes of rated U.S. firms' debt maturity structure during the sample period of 2003-2015. Both *DM3* and *DM5* show a fall in the use of long-term debt during the subprime mortgage crisis, which then gradually returns to a similar level as before the crisis. It is more difficult for firms to access long-term finance during a crisis, and firms tend to issue more short-term debt. Firms are also more exposed to refinancing and liquidation risk at the beginning of the crisis (Custódio et al., 2013). González (2015) also finds that firms that are more dependent on external finance have lower debt maturity during the crisis.

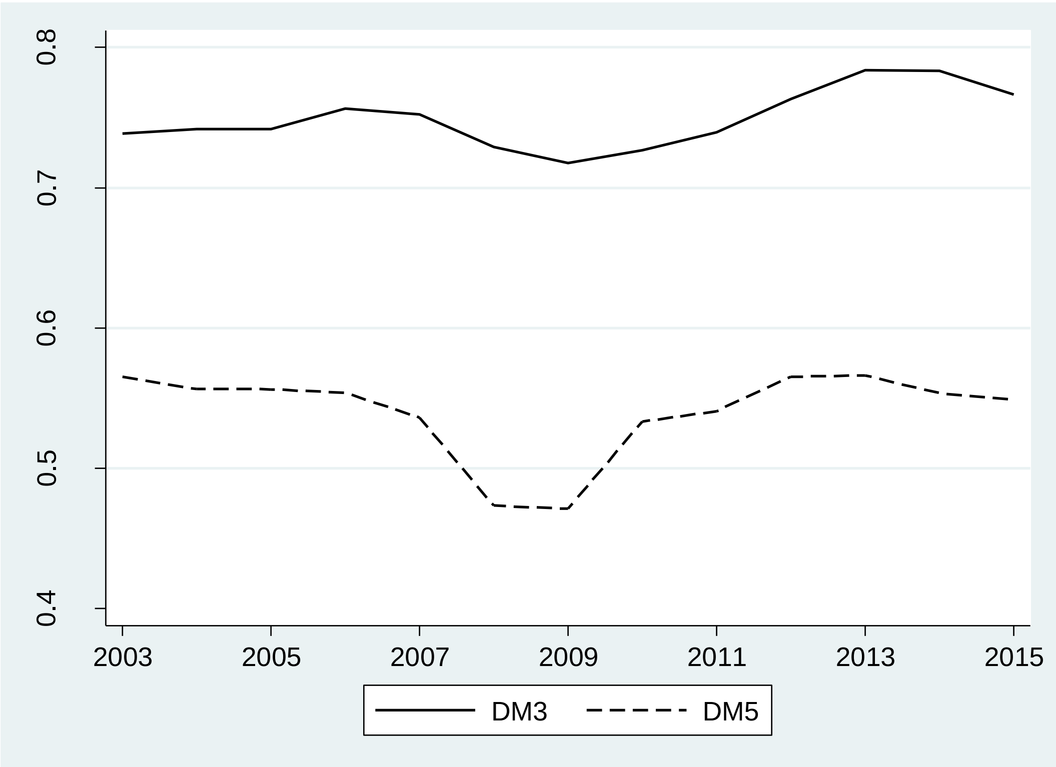


Figure 4.1. Mean of debt maturity structure. Note: The mean of debt maturity, *DM3* and *DM5*, over the sample period of 2003 – 2015.

Figure 4.2 depicts the relationship between debt maturity choices and firms' ratings. Both *DM3* and *DM5* decline slowly from the rating level 5 (B3/B–) to the rating level 20 (Aaa/AAA). This pattern is consistent with Diamond's (1991) signalling theory, which suggests that high credit quality firms tend to use more short-term debt as a signal of their financial strength. However, a striking figure of *DM5* is that firms with very low ratings (C/SD/D/CCC- ratings) have very little long-term debt. Indeed, firms with close to default or default ratings in the past year, in general, will struggle with refinancing long-term debt and are only able to issue short-term debt (if any debt), and hence display significantly lower debt maturity ratios. This is also consistent with Diamond's (1991) theory that low-credit quality firms could only borrow short-term debt, while mid-credit quality firms use more long-term debt than both lower and higher credit quality firms.

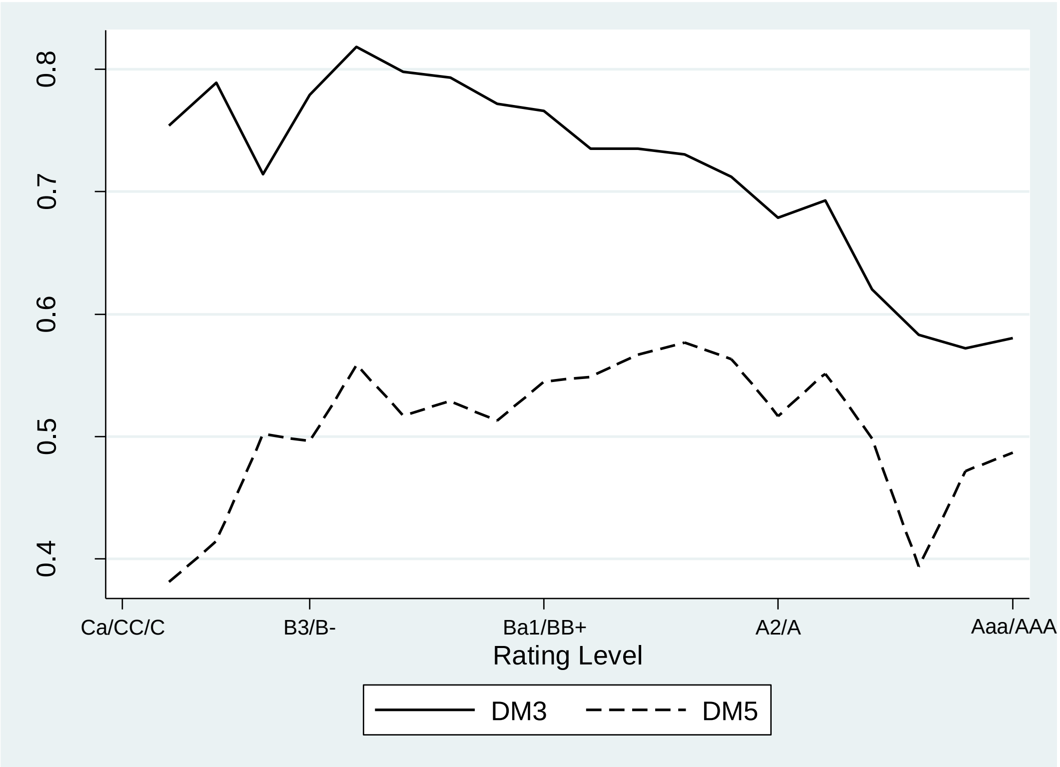
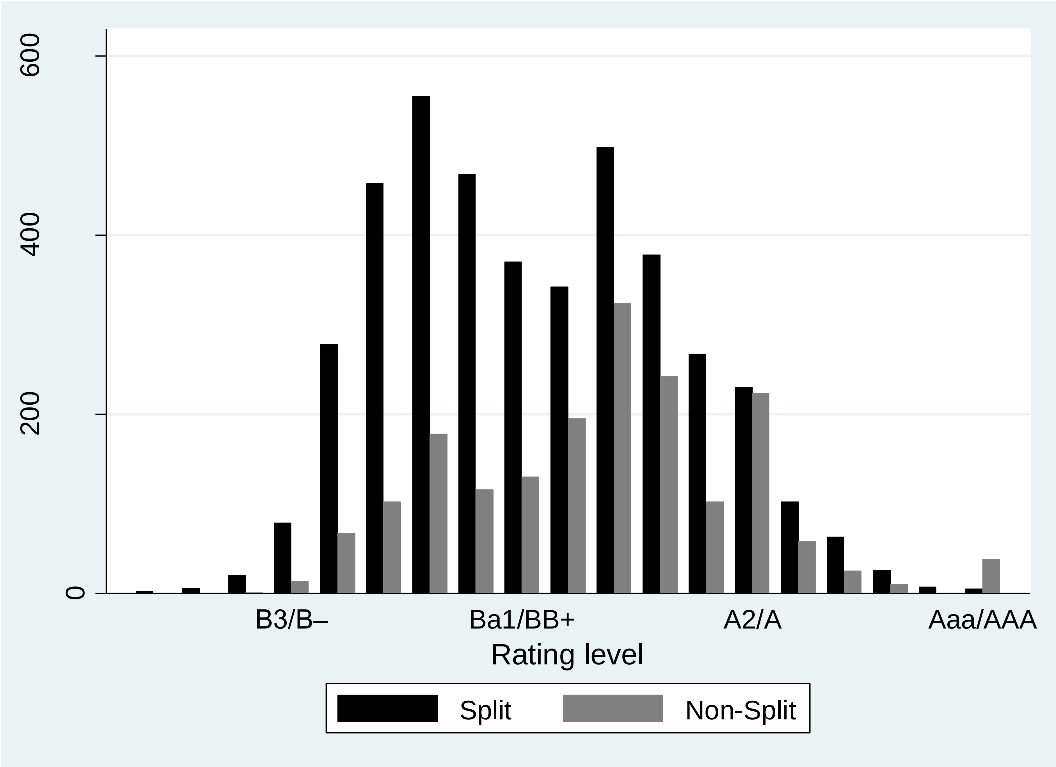


Figure 4.2. Mean of debt maturity ratios over different rating levels. Note: The mean of debt maturity (*DM3* and *DM5*) over different rating levels (20-notch scale).

Table 4.4 focuses on the split rating variables. Split ratings are common and account for approximately 70% of the total observations. Nevertheless, large annual splits are uncommon, with most annual split ratings within 1 to 3 CCR points, making up more than three quarters of split observations. The proportion of split ratings with superior S&P (Moody's) ratings of the total sample is 48.5% (19.6%). The average magnitude of the split is larger when S&P is the superior. This implies that S&P is the more generous CRA as it tends to assign more favourable U.S. corporate ratings than Moody's. This is in line with the results of Livingston et al. (2010).

Figure 4.3 presents the number of split ratings and non-split over different rating levels and years. Across different rating levels, CRAs are more likely to disagree with each other about firms' creditworthiness than agree. Moreover, there is much less disagreement for A2/A ratings and above and much more disagreement in the speculative grades. CRAs also assign different ratings more often during the boom period (2003-2006), and then they become more consistent with each other during and after the sub-prime mortgage crisis (2007-2009). CRAs' tendency to assign less-accurate ratings during booms is discussed in Bar-Isaac and Shapiro (2013).



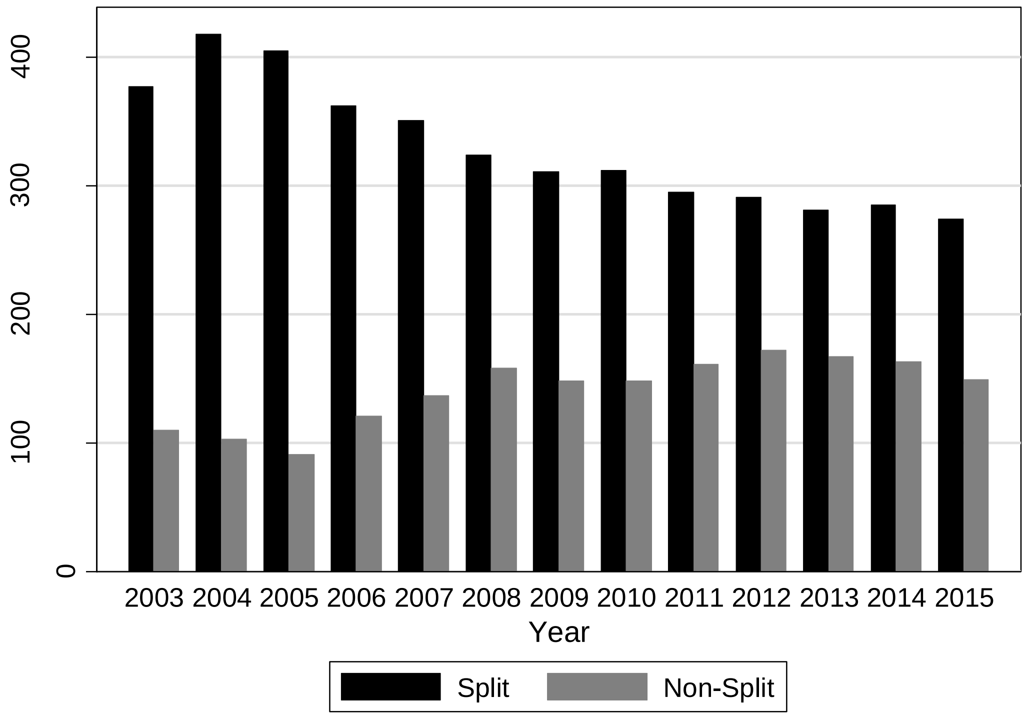


Figure 4.3. Number of split and non-split over years and different rating levels. Note: Number of split and non-split across rating categories and years. Panel A plots the number of split and non-split across rating categories; Panel B plots the number of split and non-split through the time period of the study.

4.6 Empirical results

4.6.1 Baseline model

Table 4.5 reports the results of Eq. (4.1), using the OLS, Tobit and GLM estimation approaches. The key variable of interest is the split rating variable ($ASPLIT_{t-1}$) that captures the differences in ratings between Moody's and S&P for firm *i* in year *t* – *1*. The coefficients of $ASPLIT_{t-1}$ are positive and significant. In relation to H_{1A}, these results support the information asymmetry viewpoint. Columns (I) and (II) report the results of OLS models, whereby the coefficients of $ASPLIT_{t-1}$ for *DM3* and *DM5* are 0.007 and 0.009, respectively. These positive coefficients imply that firms with larger and/or more persistent split ratings issue more long-term debt than firms without split ratings. Firms with a one-notch split rating have about 2.1% (2.7%) higher proportion of long-term debt maturing in more than 3 (5) years than non-split rated firms.[46] This suggests that split ratings have a significant effect on firms' debt maturity choices. The results of the Tobit estimation reported in Columns (III) and (IV) of Table 4.5 are consistent. Furthermore, in order to get the appropriate impact of split ratings on firms' debt maturity choices using the Tobit model, the marginal effects of the truncated expected value and of the censored expected value are calculated using Eq. (4.9) and Eq. (4.10). The results for both of them are 0.006 and 0.004, respectively and both are significant at the 5% level. The results from Tobit marginal effects still suggest that split ratings have a significant impact on firms' debt maturity.

Columns (V) and (VI) of Table 4.5 report the results of the GLM model. The coefficients for split ratings for *DM3* and *DM5* are both 0.037. The economic importance of split ratings is obtained by using marginal effects. The marginal effects of $ASPLIT_{t-1}$ on *DM3* is 0.007, implying that one-notch split leads to 0.021 or 2.1% higher debt maturity ratio (*DM3*) of split rated firms compare to non-split rated firms. Marginal effects of $ASPLIT_{t-1}$ on *DM5* is 0.009, indicating that one-notch split results in 0.027 or 2.7% higher level of long-term debt. Overall, results are very similar to the baseline model irrespective of estimation methods used.

The coefficients of the control variables have the expected sign when they are statistically significant at the 5% level. Asset tangibility ($TANG_{t-1}$) has a positive relation with debt maturity. Since tangible assets (property, plant, and equipment) are easier to value and to use as collateral, firms with a higher level of asset tangibility are more likely to issue long-term

[46] Since one-notch split is 3 CCR units, then = 3×0.007 = 2.1% and 3×0.009 = 2.7%. Note that the mean value of *ASPLIT* is 2.12 (Table 4.4).

debt. Equity issue (EI_{t-1}) also has a positive relationship with debt maturity. Firms with high levels of equity issuance are less likely to suffer from adverse selection problems. Consequently, from an information asymmetry perspective, those firms prefer to issue more long-term debt since their long-term debt is less likely to be misvalued. Industry debt maturity ($INDDM_{t-1}$) has a positive coefficient. Firms operating in an industry with a high level of debt maturity ratio prefer to issue more long-term debt, while firms operating in an industry with a lower level of debt maturity ratio issue more short-term debt.

Firms have to consider a trade-off between the favourable effect of future good news, enabling issuance of long-term debt with favourable terms, and the risk of future bad news, which leads to having to refinance with less favourable terms. Prior literature suggests that, on average, firms with split ratings are much more likely (than those with non-split ratings) to receive a further rating action in the near term (Livingston et al., 2008). Thus, a fear of future rating downgrades gives a greater incentive to split rated firms to rely on long-term debt rather than short-term debt because of the potential refinancing risk. Further, the higher long-term debt ratio of split rated firms is also beneficial in avoiding further rating downgrades, and more costly borrowing. Gopalan et al. (2014) argue that an increase in short-term debt leads to further rating deterioration as well as an increase in the cost of long-term debt borrowing. This helps to explain why firms choose to have a longer-term debt maturity structure even though they could face higher long-term borrowing costs arising from CRAs' disagreement about firms' creditworthiness. The results imply that negative rating changes and potential rollover risk pose a greater threat to split rated firms than the higher borrowing cost coinciding with split ratings, and hence firms prefer higher debt maturity ratios.

The results also suggest that CRAs' disagreement about firms' creditworthiness is a signal of firms' unfavourable private information as split rated firms tend to issue more long-term debt than non-split rated firms. This could be explained by firms' timing of releasing information. While firms with positive private information are more likely to release this news early, firms with negative private information prefer to retain it as long as possible. The action of withholding information creates the likelihood of rating disagreement between CRAs and thus split ratings could signal that firms are holding unfavourable private information about their credit quality.

4.6.2 Cross-sectional tests

To better understand the relation between split ratings and debt maturity structure, a number of cross-sectional tests are conducted. Whether the relationship between split ratings and debt maturity structure varies across different sized firms, for speculative versus investment-grade companies and through different economic conditions are examined. Following Gopalan et al. (2014), six dummies are created and interacted with $ASPLIT_{t-1}$ in an extension of Eq. (4.1). The dummy variables are *SMALL*, (*1-SMALL*), *INVST*, (*1-INVST*), *CRISIS* and (*1-CRISIS*). *SMALL* is a dummy variable equal to 1 if a firm has a below-sample-median value of *FS* in year *t – 1* and 0 otherwise. *INVST* is a dummy variable equal to 1 if a firm has an investment-grade average rating (Baa3/BBB- or above) in year *t – 1* and 0 otherwise.[47] *CRISIS* is a dummy variable equal to 1 during the U.S. sub-prime crisis period (2007 – 2009) and 0 otherwise.

Table 4.6 reports the results of Eq. (4.1) with two interaction terms, $ASPLIT_{t-1}\times SMALL$ and $ASPLIT_{t-1}\times(1\text{-}SMALL)$. The coefficients of $ASPLIT_{t-1}\times SMALL$ are insignificant while those of $ASPLIT_{t-1}\times(1\text{-}SMALL)$ are positive and significant at the 1% level, suggesting that the positive effect of split rating on debt maturity structure is predominantly associated with large firms. Agency problems are more severe in large firms than small firms and the increase in rollover risk exacerbates the conflict of interest between shareholders and debtholders (He and Xiong, 2012b). Thus, issuing more short-term debt could only worsen the situation. Therefore, large firms are less likely to rely on short-term debt when they receive different ratings from CRAs. However, the comparison of the two interaction terms' coefficients shows that they are not significantly different from each other (see the row titled ΔCOEF).

Table 4.7 reports the results of Eq. (4.1) with two interaction terms $ASPLIT_{t-1}\times INVST$ and $ASPLIT_{t-1}\times(1\text{-}INVST)$. The coefficients on $ASPLIT_{t-1}\times(1\text{-}INVST)$ are positive and significant, suggesting that longer debt maturity structure is predominantly associated with a split rating for firms with speculative-grade ratings. Since these firms face greater difficulty in refinancing or repaying their due debt (Gopalan et al., 2014), an increase in rollover risk and refinancing risk encourages split-rated firms with speculative-grade ratings to have higher debt maturity ratios. Another potential explanation is that speculative-grade firms with large amounts of long-term debt maturing within 1 year are more likely to receive more severe rating downgrades (according to Gopalan et al., 2014) and thus, they prefer to issue more long-term debt than do investment-grade split rated firms. The coefficients of the two interaction terms are significantly different from each other in 3 of the 6 cases (see the row titled ΔCOEF).

Table 4.8 reports the results of Eq. (4.1) with two interaction terms, $ASPLIT_{t-1}\times CRISIS$ and $ASPLIT_{t-1}\times(1\text{-}CRISIS)$. The results show that coefficients of $ASPLIT_{t-1}\times CRISIS$ are

[47] Firms' average ratings is calculated as the mean (rounded) of two CRAs' average ratings over the year.

positive and highly significant for DM5 not DM3 while those of $ASPLIT_{t-1}$×(1-*CRISIS*) are all positive but marginally significant. This implies that the significant effect of split ratings on debt maturity structure is somewhat stronger during the crisis period. During the sub-prime mortgage crisis, firms faced more difficulty in accessing the short-term debt market as well as facing increased rollover and refinancing risks compared to the non-crisis periods. Figure 4.1 also shows that rated firms rely more on short-term debt during the crisis and thus, split rating firms would try to avoid worsening the situation by increasing the proportion of their long-term debt over total debt. However, the coefficients of the two interaction terms are not significantly different from each other (see the row titled ΔCOEF).

4.6.3 Endogeneity

This section employs various methods to address any potential endogeneity issues.

4.6.3.1 Reverse Causality

Current changes in debt maturity might lead to a higher probability of receiving split ratings in the future. Each CRA has potentially different anticipation about firms' current financial status because of information asymmetry and therefore can assign different ratings. Further, split rated firms on average have a higher debt maturity ratio than non-split rated firms, which could result in greater information asymmetry or agency problems due to less frequent monitoring from outsiders. This information asymmetry problem could, in turn, lead to prolong or widen disagreement among CRAs on firms' creditworthiness. In order to rule out these alternative explanations, Table 4.9 presents the results of the estimation of probit and ordered probit models (Eq. (4.17)), whereby dependent variables are *SPLIT_DUM* and *ASPLIT1* respectively. *SPLIT_DUM* is a split rating dummy variable taking the value of 1 if *ASPLIT* is above zero, and *ASPLIT1* is a category variable that has four different categories corresponding to 1-, 2-, 3- and higher than 3-CCR unit split ratings of *ASPLIT*. The independent variables of particular interest are the lagged debt maturity ($DM3_{t-1}$ and $DM5_{t-1}$) and the lagged first difference of debt maturity ($\Delta DM3_{t-1}$ and $\Delta DM5_{t-1}$). The results show that their coefficients are insignificant, suggesting that the reverse effect of debt maturity on split ratings is not important.[48] Past debt maturity has no identifiable impact on the probability of subsequently having a split rating between Moody's and S&P.

[48] In addition, this test is repeated with another set of control variables, which are proven to have impact on firms' credit rating on previous literature (Gopalan et al., 2014). Appendix 4.B, Table 4.B.14 shows that the results are consistent.

4.6.3.2 Propensity Score Matching

In order to further address any potential endogeneity issue (including reverse causality/simultaneity, omitted variables), propensity score matching (PSM) is employed to construct a new matching sample which includes treated (split rated) firms and matched non-treated (non-split rated) firms. The treatment is whether or not a firm receive different opinions from CRAs (split ratings) or not. The control group involves non-split rated firms which have similar characteristics to split rated firms. In this section, various methods are presented to generate matched control and treatment groups.

Nearest-neighbour (NN) matching without replacement and with caliper set at 0.01.

In this section, NN matching without replacement and with the caliper band of 0.01 are used (Khatami et al., 2017). The caliper band of 0.01 is chosen to avoid any bad matching because the sample's number of observations is sufficient enough to trade off between increased variance and bias reduction. The propensity score is estimated using the probit regression with the dependent variable of split rated dummy (*SPLIT_DUM*), which equals one if firms are split rated at time $t - 1$ and zero otherwise. Independent variables (covariates) are firm size (*FS*), leverage (*D2A*), book value of cash over total assets (*CASH*), market-to-book value ratio (*MTB*), idiosyncratic risk (*IDIO*), taxes over total assets ratio (*TAXES*) as well as interaction terms of year and industry dummies and rating categories dummies. The final results of this PSM method is a sample of 2,478 firm-year observations equally distributed between non-split rated firms and split rated firms.

Panel A of Table 4.10 shows the descriptive statistics of unmatched and matched covariates. All the unmatched covariates have high standardised bias. *FS* and *D2A* have the highest standardised bias at about 35%. The means of the unmatched covariates between treated and control group are significantly different from each other as the t-tests between those two groups' unmatched covariate are rejected at the 1% level. After matching, the bias is reduced on every covariate as the standardised bias of all covariates is now below 5%. Nevertheless, the results suggest that the matching procedure is successful in reducing the standardised bias of the covariates. In addition, all the t-tests between the treated and control covariates of the matched sample cannot be rejected at 10% level, indicating that there are no significant differences between covariates of the treated group and those of control group and that they are balanced in both groups.

Panel B of Table 4.10 shows the result for the average treatment effect on treated (ATT) for the matched sample. ATT for *DM3* and *DM5* on the matched sample are positive and significant at the 5% level. This suggests that there is a significant difference in the mean of debt maturity between non-split rated firms and split rated firms in the matched sample. This is consistent with the baseline regression and further indicates that the matched sample is balanced and can produce unbiased results.

Panel C of Table 4.10 shows the joint significance and Pseudo R^2 test between the matched and unmatched sample. The Pseudo R^2 value in the matched sample is only 1.2%, which is fairly low compared to the 11.2% of that of the unmatched sample. In addition, the F-test on the joint significance of all covariates of the matched sample suggests that the null hypothesis that all the means of covariates are equal cannot be rejected, further indicating that the covariates are balanced in both treated and control groups. Overall, the standardised bias test, t-test as well as the joint significance test confirm that the propensity score specification is sufficient, and the matched sample is well balanced.

Table 4.11 shows the results of the probit regression (Eq. (4.17), column (I)) and of Eq. (4.1) with the matched sample (column (II) to (VII)) using the OLS, Tobit and GLM approaches. In column (I), the coefficients of *IDIO* and *D2A* are positive and significant at the 1% level, suggesting that firms with high returns volatility and high leverage are more likely to be split rated. The coefficient on *TAXES* is negative and significant at the 1% level, suggesting that firms with more tax expenses are less likely to be split rated. The results of Eq. (4.1) re-estimation reported in Column (II) to (VII) are similar to those of the baseline model. The coefficients of $ASPLIT_{t-1}$ are positive and significant at the 5% level across different models from Column (II) to (VII) and thus they are consistent with the finding that split rated firms are more likely to have a higher level of long-term debt than non-split rated firms.

NN matching with replacement and with caliper set a 0.01.

In the previous method, NN matching is employed without replacement as the sample observations are large enough to trade-off the increase in variance (decreased number of observations) for bias reduction. However, in the main sample, the number of treated units (split rated observations) (4,690) is much higher than the number of control units (non-split rated observations) (1,940). Thus, in this case, it would be sensible to use the NN matching with replacement approach, in which control units can be used to match with multiple treated units. Tables 4.12 and 4.13 reports the various matching quality tests and the main regression

(Eq. (4.1)) results for the NN matching with replacement and with the caliper band of 0.01.[49] Results on the matched sample with replacement are consistent with the baseline results and the results of the matched sample without replacement, suggesting that our PSM gives similar results irrespective to which trade-off is used, reduce variance – increase bias or reduce bias – increase variance.

Other matching methods

In addition to NN matching, various matching approaches – including radius matching, kernel matching and Mahalanobis matching, are used as additional robustness tests. Tables 4.B.1 and 4.B.2 in Appendix 4.B present the matching quality and regression results (Eq. (4.1)) for the radius matching method. Similar to NN matching methods, the results for the radius matching sample are consistent with the main results.

Tables 4.B.3 and 4.B.4 in Appendix 4.B presents the matching quality investigation and regression results (Eq. (4.1)) for kernel matching using Epanechnikov kernel function and bandwidth of 0.06.[50,51] Similar to the previous matching method, the results from kernel matching are consistent with the baseline results, suggesting that the main results are robust.

Tables 4.B.5 and 4.B.6 in Appendix 4.B reports the matching results for the Mahalanobis matching. In this method, the observations are ordered randomly and then the distance between treated units and control units is calculated. Treated unit and control unit are matched based on the smallest Mahalanobis distance and smaller than the 0.01 caliper band. Following Almeida et al. (2017), the covariates are used without the *YEAR*INDUSTRY* interaction term and rating level dummies due to the fact that additional covariates increase the difficulty of finding a Mahalanobis matched control group for the treated group.[52] Table 4.B.5 reports the quality of Mahalanobis matching procedure. All covariates satisfy the standardised bias and the t-test, suggesting that the chosen covariates and matching method are suitable for the data structure. Table 4.B.6 reports the regression using Eq. (4.1) with the matching sample using Mahalanobis matching (Column (I) to (VI)). They show that the results from

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[49] Two covariates, *IDIO* and *TAXES*, are removed and replaced by *TANG* in the probit model to calculate propensity score because they do not satisfy the standardised bias and the selection bias tests.
[50] The chosen bandwidth is 0.06 to avoid oversmoothed estimates using large bandwidth or undersmoothed estimates using low bandwidth. In addition, kernel matching procedure is repeated with different bandwidths (0.01, 0.03, 0.1, and 0.2) and the regression results are still consistent with one with the bandwidth of 0.06 as well as the baseline model.
[51] For kernel matching, *TAXES* variable is used instead of *D2A* as *D2A* do not satisfy the standardised bias test.
[52] Covariates used for Mahalanobis matching are *FS*, *D2A*, *CASH*, *TANG*, *MTB* and *TAXES*.

Mahalanobis matching are consistent with the baseline results, indicating that the main results are robust.

Overall, results are very similar regardless of which matching techniques used. Moreover, the matching results further confirm that this chapter's findings are unaffected by potential endogeneity issues.

4.6.4 Additional robustness tests

4.6.4.1 Different variable definions and different samples.

In the main regression, split ratings are rounded to the nearest integer to remove the impact of short-lived split ratings. However, by doing so, higher split ratings are also effectively smoothed and thus, could lead to biased estimation. In order to rule out this issue, the main model (Eq. (4.1)) is estimated with a new definition of split ratings, for which only below 0.5 split is rounded. Table 4.B.7 in Appendix 4.B reports the results of Eq. (4.1) with the new split ratings (*ASPLIT1*), which are only rounded for any split below 0.5. The coefficients of *ASPLIT1* are positive and significant at the 5% level, which is consistent with the results of the baseline model.

In Section 4.5.1, when calculating *DM3*, *DM5*, and *RD*, missing values of *dd*, *dd1*, *dd2*, *dd3*, *dd4*, and *dd5* are set to be zero. As a robustness test, Eq. (4.1) is re-estimated with new *DM3* and *DM5*, which are calculated using Eq. (4.3) and Eq. (4.4) excluding missing *dd*, *dd1*, *dd2*, *dd3*, *dd4*, and *dd5*. The results, reported in Table 4.B.10 in Appendix 4.B, are robust.

Eq. (4.1) is also re-estimated with the new *RD* variable calculated by excluding missing *xrd*. Results (reported in Table 4.B.11 in Appendix 4.B) show that the coefficients for the split ratings variable (*ASPLIT*) are positive and significant at the 1% level, suggesting the baseline results are robust regardless of *RD* specification (whether excluding missing *xrd* or not).

Prior capital structure and debt maturity literature (e.g. Frank and Goyal, 2009; Keefe and Yaghoubi, 2016) excludes financial companies (SIC codes 6000-6999) or utilities (SIC codes 4900-4999) from the main sample because the financial structure of these firms is significantly different from nonfinancial firms. In the main results, financial and utilities firms are included in the sample as ratings are likely to have an effect on those firms as well as industrial firms (Kisgen, 2006). However, following Petacchi (2015), Eq. (4.1) is estimated using a sub-sample that excludes financial firms or a sub-sample excluding utilities and Tables

4.B.12 and 4.B.13 in Appendix 4.B presents the results from those sub-samples, respectively.[53] The coefficients of *ASPLIT* in both Tables 4.B.12 and 13 are positive and significant.

Table 4.B.14 in Appendix 4.B reports results using Eq. (4.1) with the logit transformation of *DM3* and *DM5*, *LnDM3* and *LnDM5*, respectively. The coefficient of split ratings (*ASPLIT*) in both models are positive but only significant at the 5% level for *LnDM3*. This result could be affected by the drawback of the logit transformation that it will fail to capture the effect when *DM3* and *DM5* equal to 0 and 1 (in the sample, the number of DM3 observations that equals to 0 or 1 is 571 and that of DM5 is 638).

4.6.4.2 Livingston and Zhou's (2010) methodology

Similar to Chapter 3, the research design of this Chapter faces a potential problem of using rounded average ratings from Moody's and S&P as rating levels. Thus, this Chapter also employs the approach used by Livingston and Zhou (2010) to deal with this issue in a robustness test. Appendix 4.C provides details on the design and empirical results based on this setup.

Table 4.C.1 in Appendix 4.C reports the results of testing the superior and inferior model using Eq. (4.C.1) and Eq. (4.C.2). The coefficients on the split rating variables (*ASPLIT*) for both superior and inferior rating models are positive and significant, suggesting that the actual level of debt maturity of split rated firms is higher than the estimated level of debt maturity of these firms if both CRAs had assigned the same ratings, inferior or superior ratings. On average, one-notch split rated firms have 1.8% higher level of debt maturity than the average of estimated debt maturity of these firms if both CRAs had assigned the same superior ratings/inferior ratings. This is consistent with the baseline results, suggesting that the main model is robust. This additional test helps to reinforce the main findings of this chapter.

[53] Robustness tests with exclusion of both financial and utility firms are consistent with the baseline model.

4.7 Superior S&P ratings versus superior Moody's ratings and firms' debt maturity

Table 4.14 reports the results of Eq. (4.2), using the OLS, Tobit and GLM estimation approaches, to examine H_{2A}, i.e. whether firms' behaviour differs based on a specific more generous CRA. The key variable of interest is SUP_MOODY_{t-1} ($SUP\_S\&P_{t-1}$), which are dummy variables equal to 1 if Moody's (S&P) rating is higher than S&P (Moody's) and 0 otherwise. The coefficients for SUP_MOODY_{t-1} are negative and marginally significant in most of the cases, while the coefficients for $SUP\_S\&P_{t-1}$ are positive and significant at the 5% level in every estimation. The negative relationship between SUP_MOODY_{t-1} and *DM3* (*DM5*) suggests that firms with superior Moody's ratings use more short-term debt than non-split rated firms and firms with superior S&P ratings. The coefficients of $SUP\_S\&P_{t-1}$ for *DM3* and *DM5* in the OLS models are 0.025 and 0.030, respectively. This implies that one-notch split rated firms with superior S&P ratings have 7.5% (9%) higher ratio of long-term debt maturing in more than 3 (5) years (over total debt) than non-split rated firms or split rated firms with superior Moody's ratings.[54] In addition, the comparison of the coefficients on the two key variables of interest suggests that the two coefficients are significantly different from each other (see the row titled ΔCOEF).

Given that Moody's is the more conservative CRAs in this data sample and that both CRAs have become more conservative during the sample period (Baghai et al., 2014), one might expect that when S&P ratings are superior to Moody's, they are more likely to be downgraded to Moody's level. The results confirm this view. The positive and significant coefficient on $SUP\_S\&P_{t-1}$ suggests that firms with superior S&P ratings tend to be more concerned about being downgraded in the future and thus they are more likely to have a higher level of long-term debt in anticipation of this. Further, firms rely more on long-term debt than short-term debt when they have negative private information about their credit quality in the future (Goyal and Wang, 2013). Hence, the results imply that firms with superior S&P ratings are relatively more likely to have negative private information about their credit risk while firms with superior Moody's ratings are relatively more likely to have positive private information about their credit risk.

[54] Since one-notch split is 3 CCR units, then 3*0.025 = 7.5% and 3*0.030 = 9%.

4.8 Conclusions

This Chapter investigates whether split ratings have any impact on corporate debt maturity decisions. A sample including all listed U.S. corporations that have long-term credit ratings from both Moody's and S&P from 2003 to 2015 is used. In the sample, firms have an average long-term debt ratio of 75%, which confirms that rated firms rely heavily on long-term borrowing. In addition, about 70% of observations are split rated and thus CRAs' disagreement upon firms' creditworthiness is very common. The descriptive statistics of split ratings also show that Moody's is a more conservative CRA than S&P, whereby 48% of firms with split ratings have superior S&P ratings compared to a figure of 20% with superior Moody's ratings.

This Chapter hypothesizes that disagreement between CRAs about firms' creditworthiness could have a significant impact on firms' optimal debt maturity structure. On one hand, firms could choose to use more short-term debt to avoid costly long-term borrowing cost arising from split ratings and by doing so, they at the same time could signal their financial strength and reduce their information asymmetry problems. As a result, under this viewpoint, split rated firms might have a lower debt maturity ratio than their non-split rated peers. On the other hand, firms could rely more on borrowing at the long end of the spectrum due to the risk of inability to roll-over maturing debt. Thus, under this viewpoint, firms with split ratings might have a higher proportion of long-term debt over total debt compared to firms without split ratings. This Chapter provides empirical evidence on the competing views.

Table 4.15 provides a brief summary of this Chapter's empirical findings. This Chapter reveals that split rated firms are, on average, more likely to have higher debt maturity ratios than non-split rated firms, and this effect is consistent across different estimation approaches and robustness tests. One-notch split rated firms have about 2.1% higher long-term debt ratios than their non-split rated peers. The results are primarily revealed in larger firms and those with speculative-grade ratings. Moreover, the impact of split ratings on debt maturity is somewhat stronger during the sub-prime crisis period. Gopalan et al. (2014) argue that firms with more shorter-term debt profiles experience higher possibility of rating deterioration and higher cost of long-term borrowing. Thus, the fear of future rating downgrades and potentially higher borrowing costs are key factors inducing firms to choose longer-term debt to avoid rollover on less favourable terms. This finding offers new empirical evidence to inform the debate on whether firms choose between issuing long-term debt (accepting a potentially higher cost of long-term debt arising from split ratings) and issuing short-term debt (with a risk of negative unexpected rating change and higher future cost of debt). The results imply that firms place more emphasis on potential rollover risk coinciding with unexpected future rating downgrades than on the immediate higher cost of long-term debt caused by CRAs' different credit opinions. This is consistent with information asymmetry models (Flannery, 1986; Diamond, 1991; Goyal and Wang, 2013), which argue that firms with unfavourable private information prefer to borrow at the long end of the maturity spectrum. The results are also consistent with Goyal and Wang's (2013) findings that firms with unfavourable private information about their default risk are more likely to issue long-term debt because those firms anticipate negative future rating changes.

In addition, firms with superior S&P ratings tend to have a higher debt maturity ratio than firms with superior Moody's ratings. This suggests that firms with superior S&P ratings are more likely to have negative private information and therefore, they are more likely to worry about future negative rating changes and decide to use more long-term debt as an anticipation of this potential rating deterioration. The result is consistent with Baghai et al.'s (2014) finding that CRAs become more conservative during the sample period and Goyal and Wang's (2013) finding that firms will rely more on long-term debt if they have negative private information.

This Chapter employed various robustness tests including propensity score matching and reverse causality to rule out the potential issues arising from endogeneity. Furthermore, additional robustness tests are employed to address the specification of debt maturity variables, key explanatory variable, control variables and main sample definitions. Inferences from these tests are also very similar to the baseline model irrespective of different definitions or different estimation methods used. Despite this array of tests, the baseline results hold throughout.

The study offers novel contributions to the existing literature on debt maturity and credit ratings. It confirms the importance of both major CRAs, for firms, debt markets and real economic outcomes, despite some negative recent perceptions of CRAs' credibility. The findings indicate that the ratings from both CRAs contribute additional information to the credit market and the differences between the two CRAs provide incremental value-relevant information to firms. Split rated firms could issue more short-term debt to demonstrate financial strength and at the same time, avoid high long-term borrowing cost if they have favourable private information about their default risks. In addition, firms with split ratings could rely more on bank financing than public debt. As the results suggest that split rated firms are more concerned about the future financial constraints (rating downgrades), bank debt could be more appealing to such firms since it is a more flexible financing source and firms with a larger proportion of bank financing are less sensitive to rating downgrades (Bedendo and Siming, 2018). For investors, split ratings (especially, when S&P assign superior ratings) could be an indication about firms' negative private information about their credit risks, and thus, investors could anticipate potential future changes in firms' ratings and demand a premium for such extra risks. For regulators, it is further evidence of the need to take into account the behaviour and actions of multiple CRAs.

Table 4.1. Variable Definitions

Variable	Definition	Construction	Data Sources
DM3	DM3 is the ratio of long-term debt (*dltt*) minus debt maturing in the second and third year (*dd2* and *dd3*) to total debt.	$DM3 = \frac{dltt - dd2 - dd3}{dltt + dlc}$	Compustat
DM5	DM5 is the ratio of the long-term debt minus debt maturing in the second, third, fourth and fifth year (*dd2*, *dd3*, *dd4* and *dd5*) to total debt.	$DM5 = \frac{dltt - dd2 - dd3 - dd4 - dd5}{dltt + dlc}$	Compustat
ASPLIT	Absolute split ratings are the rounded average of absolute daily differences between Moody's and S&P over a calendar year. More than 4-CCR unit ASPLIT is set to be 4.	|Moody's rating – S&P rating|	Moody's website and Capital IQ
SPLIT	Split ratings are the average of daily differences between Moody's and S&P over a calendar year.	(Moody's rating – S&P rating)	Moody's website and Capital IQ
SUP_MOODY	SUP_MOODY is a dummy variable, taking the value of 1 if SPLIT > 0 (Moody's rating is superior to S&P) and, 0 otherwise.	SUP_MOODY = 1 if SPLIT > 0 SUP_MOODY = 0 if SPLIT <= 0	Moody's website and Capital IQ
SUP_S&P	SUP_S&P is a dummy variable, taking the value of 1 if SPLIT < 0 (S&P rating is superior to Moody's rating) and, 0 otherwise.	SUP_S&P = 1 if SPLIT < 0 SUP_S&P = 0 if SPLIT >= 0	Moody's website and Capital IQ
MTB	Market to book ratio is the ratio of market value of asset to total assets (González, 2015; Ben-Nasr et al., 2015; Huang et al., 2016).	$\frac{MVA}{at}$ [55]	Compustat
TANG	Firms' assets tangibility (Lemmon et al., 2008; Kirch and Terra, 2012).	$\frac{ppent}{at}$	Compustat
PROFIT	Profitability of a firm (Frank and Goyal, 2009).	$\frac{oibdp}{at}$	Compustat
FS	Firm size is the natural log of total assets (Ben-Nasr et al., 2015; Díaz-Díaz et al., 2016; Huang et al., 2016).	*ln(at)*	Compustat
CASH	The ratio of book value of cash and marketable securities to the book value of total assets.	$\frac{che}{at}$	Compustat
D2A	The ratio of total debt to total assets.	$\frac{dlc + dltt}{at}$	Compustat

[55] *MVA = dlc + dltt + ppstkl + csho*prcc_f – txditc*. Details of Compustat items can be found in the Appendix 4.A.

Table 4.1. Continued.

Variable	Definition	Construction	Data Sources
R&D	Ratio of R&D expenses to sale. (Keefe and Yaghoubi, 2016)	$ln(1 + [xrd/sale])$	Compustat
AGE	Firm age is the natural logarithm of the number of years that the firm has been operating since the founding year.	ln(current year – founding year)	Capital IQ
EI	Equity issue is the split-adjusted change in shares outstanding times the split-adjusted average stock price divided by the end of year *t – 1* total assets (Lemmon et al., 2008).	$EI_{i,t} = [csho_t - csho_{t-1} \times (ajex_{t-1}/ajex_t)] \times [prccf_t + prccf_{t-1} \times (ajex_t/ajex_{t-1})]/at$	Compustat
TAXES	The ratio of tax expenditure to book value of total assets.	$\frac{txt}{at}$	Compustat
BETA	Firm systematic risk	BETA is calculated using monthly returns over the lagged 5 years.[56]	Compustat
IDIO	The standard deviation of the prior year's monthly returns.	The SD of firms' past year's monthly returns[57]	Compustat
INDDM	The median industry debt maturity of the sector in which a firm is classified by 4-digit SIC code.	The median of DM3	Compustat
LEVEL	Set of 19 dummy variables representing the rating categories of a firm calculated as the rounded annual average of Moody's and S&P daily ratings	Rounded value of ([Moody_Rating + S&P_Rating]/2)	Moody's website and Capital IQ
YEAR*INDUSTRY	Interactions between two dummy groups, YEAR and INDUSTRY, to control for the macro-economic changes.	YEAR: is a set of dummy variables equal to 1 for the given year and 0, otherwise. INDUSTRY: is a set of dummy variables for 1-digit SIC industries.[58]	Compustat

Note: Table 4.1 provides the definitions of all used variables and data sources.

[56] BETA could be obtained from Compustat database by creating two custom concepts: total monthly return; TRT1M = (((*prccm***trfm*)/(*prccm***trfm*)[-1])-1)*100; and BETA = (@PCOR(TRT1M,"I0003":TRT1M,-59,0)*@PSTD(TRT1M,-59,0))/(@PSTD("I0003":TRT1M,-59,0)).

[57] IDIO could be obtained from Compustat database by creating a concept: IDIO = @PSTD(TRT1M,-12,0).

[58] 1-digit SIC industry dummies are used to persevere the degree of freedom as the interactions between YEAR and INDUSTRY increase the number of variables used exponentially. However, robustness tests estimating Eq. (4.1) and Eq. (4.1) with 2-digit SIC industry and 3-digit SIC industry dummies produce similar results.

Table 4.2. Sampling process

Sampling			
Filter	Criterion	# of Firm-Years	# of Unique Firms
1	All rated U.S. firms available in Compustat	9,409	1,404
		-41	-5
2	Remove firms involved in a major merger/acquisition	9,368	1,399
		-592	-24
3	Remove any observations with negative common/ordinary equity	8,776	1,375
		-1,137	-346
4	Remove any missing dependent variables	7,639	1,029
		-1,031	-145
6	Remove any missing control variables	6,630	884
		0	0
7	Winsorize dependent variables and control variables at 0.5^{th} and 99.5^{th} percentile	6,630	884
Final sample		6,630	884

Note: The table presents the sample selection procedure for all rated U.S. corporations from 2003 to 2015.[59]

[59] There were 143 financial firms in the initial sample. 134 of those were removed due to missing dependent and control variables.

Table 4.3. Summary statistics and pairwise correlations

Panel A. Summary statistics.

Variables	N	Mean	Std. Dev	Min	Max	p25	Median	p75
DM3	6,630	0.74	0.24	0.00	1.00	0.62	0.80	0.94
DM5	6,630	0.54	0.30	0.00	1.00	0.34	0.57	0.76
TANG	6,630	0.37	0.25	0.02	0.93	0.15	0.30	0.58
FS	6,630	8.48	1.38	5.36	12.17	7.49	8.36	9.44
MTB	6,630	1.23	0.68	0.34	4.70	0.78	1.05	1.47
PROFIT	6,630	0.13	0.06	-0.09	0.36	0.09	0.12	0.17
RD	6,630	0.02	0.04	0.00	0.25	0.00	0.00	0.01
EI	6,630	-0.03	0.51	-3.65	2.23	-0.03	0.00	0.03
AGE	6,630	3.81	0.96	0.00	5.89	3.14	4.01	4.60
INDDM	6,630	0.49	0.31	0.00	1.00	0.23	0.57	0.76
No. of firms	884							

Panel B. Pairwise correlations.

	ASPLIT	TANG	FS	MTB	PROFIT	RD	EI	AGE	INDDM
ASPLIT	1								
TANG	0.0033	1							
FS	-0.2055***	0.0110	1						
MTB	-0.0289**	-0.1759***	-0.0026	1					
PROFIT	-0.0857***	0.0086	0.0134	0.5593***	1				
RD	0.0245**	-0.3247***	0.1294***	0.2839***	0.0251**	1			
EI	0.0371***	0.0498***	-0.0449***	-0.1589***	-0.2231***	0.0266**	1		
AGE	-0.0654***	-0.1496***	0.2374***	0.0126	0.0819***	-0.0016	-0.1037***		
INDDM	-0.0249**	0.3349***	0.0824***	-0.1843***	-0.0696***	-0.4285***	-0.0245**	0.0511***	1

Note: This table provides the descriptive statistics and the pairwise correlations of the sample, which includes all U.S. listed firms rated by Moody's and S&P during 2002–2015. See Table 4.1 for variables' definitions. Variables are winsorized at 0.5^{th} and 99.5^{th} percentile (except for *ASPLIT*, and *INDDM*). Summary statistics for *ASPLIT*, *SUP_MOODY* and *SUP_S&P* are presented in Table 4.5. ***, **, and * refer to significant coefficients at the 1%, 5%, 10% levels, respectively.

Table 4.4. Statistical properties and distributions of annual split ratings

	N	Mean	Std. Dev	Min	Max	1 CCR (%)	2 CCR (%)	3 CCR (%)	4 CCR (%)	5 CCR (%)	6 CCR (%)	7 CCR 9 CCR (%)	10 CCR 12 CCR (%)	>= 13 CCR (%)	Split total (%)
Panel A. Absolute split ratings															
ASPLIT	6,630	2.120	2.183	0	19	17.3	14.0	22.0	5.4	3.7	5.1	1.5	0.7	0.3	70.0
Panel B. Split ratings															
SPLIT	6,630	-1.139	2.774	-17	19	16.7	13.1	21.2	5.3	3.5	5.0	2.5	0.6	0.2	68.1
Moody’s > S&P	1,302	2.324	1.509	1	19	38.6	20.7	29.6	5.3	2.1	1.7	1.5	0.2	0.5	
S&P > Moody’s	3,215	3.290	2.080	1	17	18.8	18.7	31.8	8.7	6.4	9.7	4.4	1.2	0.3	

Note: The table presents the descriptive statistics and the distribution of absolute annual split ratings between Moody’s and S&P. Firms’ ratings are transformed into numerical ratings using 58-point comprehensive credit ratings (CCR) scale. Split ratings are computed as daily CCR differences (Moody’s rating minus S&P rating), averaged over the calendar year for each corporation, and rounded to the nearest integer. Similar to annual split ratings, absolute split ratings use absolute daily CCR differences to calculate split ratings. 1 CCR (%), …,7 CCR – 9 CCR (%), 10 CCR – 12 CCR (%), and >=13 CCR (%) columns indicate the magnitudes of split ratings in CCR units. Split total (%) column indicates the percentage of split ratings to the total number of observations.

Table 4.5. Split ratings and debt maturity

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	DM5 (II)	DM3 (III)	DM5 (IV)	DM3 (V)	DM5 (VI)
$ASPLIT_{t-1}$	+	0.007**	0.009**	0.007**	0.009**	0.037**	0.037**
		(2.37)	(2.37)	(2.20)	(2.27)	(2.35)	(2.39)
$TANG_{t-1}$	+	0.055**	0.067*	0.067**	0.082**	0.311**	0.277*
		(2.06)	(1.73)	(2.34)	(2.01)	(2.06)	(1.75)
FS_{t-1}	+	-0.005	0.011	-0.008	0.015**	-0.024	0.044*
		(-0.91)	(1.64)	(-1.42)	(2.12)	(-0.88)	(1.65)
MTB_{t-1}	-	-0.006	0.010	-0.006	0.011	-0.029	0.041
		(-0.60)	(0.81)	(-0.51)	(0.83)	(-0.53)	(0.81)
$PROFIT_{t-1}$	-	0.115	-0.064	0.124	-0.058	0.631	-0.267
		(1.32)	(-0.56)	(1.27)	(-0.45)	(1.31)	(-0.57)
RD_{t-1}	-	0.035	0.068	0.058	0.040	0.242	0.278
		(0.19)	(0.33)	(0.29)	(0.17)	(0.27)	(0.33)
EI_{t-1}	+	0.019***	0.022***	0.020***	0.023***	0.100***	0.091***
		(3.19)	(2.85)	(3.00)	(2.67)	(3.30)	(2.87)
AGE_{t-1}	+	-0.005	0.003	-0.008	0.001	-0.030	0.011
		(-0.87)	(0.36)	(-1.33)	(0.14)	(-0.95)	(0.36)
$INDDM_{t-1}$	+	0.096***	0.086***	0.094***	0.094***	0.505***	0.349***
		(4.82)	(3.14)	(4.38)	(3.13)	(4.85)	(3.15)
Constant		0.176***	0.186***	0.185***	0.150**	-1.351***	-2.205***
		(3.69)	(2.92)	(3.64)	(2.18)	(-5.11)	(-8.41)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		884	884	884	884	884	884

Note: Table 4.5 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches. The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time t. The main independent variable is the split rating (*ASPLIT*), which is the rounded value of the absolute average daily rating differences between Moody's and S&P at time *t-1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.6. Large firms and small firms

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	*DM5* (II)	*DM3* (III)	*DM5* (IV)	*DM3* (V)	*DM5* (VI)
$ASPLIT_{t-1} \times SMALL_{t-1}$	+	0.005	0.004	0.005	0.004	0.023	0.017
		(1.14)	(0.80)	(1.05)	(0.68)	(1.04)	(0.81)
$ASPLIT_{t-1} \times (1\text{-}SMALL_{t-1})$	+	0.009***	0.014***	0.009***	0.015***	0.049***	0.057***
		(2.82)	(3.18)	(2.64)	(3.22)	(2.87)	(3.22)
$TANG_{t-1}$	+	0.055**	0.066*	0.067**	0.082**	0.310**	0.275*
		(2.05)	(1.71)	(2.33)	(1.99)	(2.05)	(1.74)
FS_{t-1}	+	-0.007	0.006	-0.010*	0.009	-0.038	0.023
		(-1.22)	(0.79)	(-1.65)	(1.18)	(-1.22)	(0.79)
MTB_{t-1}	-	-0.007	0.009	-0.006	0.011	-0.030	0.039
		(-0.63)	(0.75)	(-0.53)	(0.78)	(-0.56)	(0.76)
$PROFIT_{t-1}$	-	0.119	-0.057	0.127	-0.050	0.649	-0.238
		(1.36)	(-0.49)	(1.30)	(-0.39)	(1.34)	(-0.50)
RD_{t-1}	-	0.032	0.061	0.055	0.033	0.225	0.251
		(0.17)	(0.29)	(0.27)	(0.14)	(0.25)	(0.30)
EI_{t-1}	+	0.019***	0.022***	0.020***	0.022***	0.099***	0.089***
		(3.16)	(2.80)	(2.98)	(2.62)	(3.27)	(2.82)
AGE_{t-1}	+	-0.005	0.003	-0.008	0.001	-0.030	0.011
		(-0.88)	(0.34)	(-1.34)	(0.12)	(-0.95)	(0.34)
$INDDM_{t-1}$	+	0.096***	0.086***	0.094***	0.095***	0.508***	0.352***
		(4.85)	(3.18)	(4.40)	(3.17)	(4.89)	(3.19)
Constant		0.200***	0.237***	0.210***	0.207***	-1.212***	-1.992***
		(3.61)	(3.21)	(3.54)	(2.59)	(-3.98)	(-6.58)
ΔCOEF		0.004	0.010	0.004	0.011	0.026	0.040
		(0.96)	(2.42)	(0.87)	(2.68)	(1.06)	(2.53)
Prob > F (χ^2)		0.327	0.120	0.352	0.102	0.303	0.111
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		884	884	884	884	884	884

Note: Table 4.6 reports the results for Eq. (4.1) with two interaction term, $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1\text{-}SMALL_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1\text{-}SMALL_{t-1})$, where $SMALL_{t-1}$ is a dummy that identifies firms with below-sample-median value of firm size (*FS*). The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt. The control variables are asset tangibility (TANG), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. The tests of the differences between two interaction terms are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (For ΔCOEF, F-test in Column (I) to (VI) and χ^2-test for Column (V) and (VI)). Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.7. Investment-grade firms and speculative-grade firms

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	*DM5* (II)	*DM3* (III)	*DM5* (IV)	*DM3* (V)	*DM5* (VI)
$ASPLIT_{t-1} \times INVST_{t-1}$	+	0.003	0.002	0.003	0.002	0.016	0.008
		(0.70)	(0.38)	(0.71)	(0.35)	(0.77)	(0.39)
$ASPLIT_{t-1} \times (1\text{-}\ INVST_{t-1})$	+	0.010***	0.014***	0.010**	0.015***	0.056**	0.059***
		(2.61)	(2.73)	(2.36)	(2.60)	(2.54)	(2.75)
$TANG_{t-1}$	+	0.055**	0.067*	0.067**	0.083**	0.312**	0.278*
		(2.07)	(1.74)	(2.35)	(2.02)	(2.06)	(1.76)
FS_{t-1}	+	-0.005	0.010	-0.008	0.014**	-0.025	0.043
		(-0.96)	(1.59)	(-1.46)	(2.06)	(-0.92)	(1.60)
MTB_{t-1}	-	-0.006	0.010	-0.006	0.011	-0.028	0.042
		(-0.60)	(0.82)	(-0.50)	(0.85)	(-0.51)	(0.83)
$PROFIT_{t-1}$	-	0.111	-0.072	0.120	-0.066	0.606	-0.299
		(1.27)	(-0.62)	(1.23)	(-0.52)	(1.25)	(-0.63)
RD_{t-1}	-	0.041	0.079	0.065	0.053	0.280	0.325
		(0.23)	(0.38)	(0.32)	(0.22)	(0.31)	(0.39)
EI_{t-1}	+	0.020***	0.023***	0.020***	0.023***	0.101***	0.093***
		(3.24)	(2.91)	(3.05)	(2.73)	(3.36)	(2.93)
AGE_{t-1}	+	-0.005	0.002	-0.008	0.001	-0.031	0.010
		(-0.90)	(0.32)	(-1.35)	(0.11)	(-0.98)	(0.32)
$INDDM_{t-1}$	+	0.095***	0.085***	0.093***	0.093***	0.503***	0.346***
		(4.80)	(3.12)	(4.36)	(3.11)	(4.83)	(3.13)
		0.003	0.002	0.003	0.002	0.016	0.008
Constant		0.170***	0.175***	0.179***	0.138**	-1.393***	-2.250***
		(3.57)	(2.75)	(3.52)	(2.00)	(-5.28)	(-8.58)
ΔCOEF		0.007	0.012*	0.007	0.013*	0.040	0.051*
		(1.74)	(3.00)	(1.44)	(2.99)	(1.96)	(3.02)
Prob > F (χ^2)		0.188	0.084	0.230	0.084	0.161	0.082
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		884	884	884	884	884	884

Note: Table 4.7 reports the results for Eq. (4.1) with with two interaction term, $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1\text{-}\ INVST_{-1})$. The key variables of interest are $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1\text{-}\ INVST_{t-1})$, where $INVST_{t-1}$ is a dummy that identifies firms with an investment-grade rating. The dependent variables DM3 (DM5) are the ratio of long-term debt maturing in more than 3 (5) years over total debt. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. The tests of the differences between two interaction terms are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (For ΔCOEF, F-test in Column (I) to (VI) and χ^2-test for Column (V) and (VI)). Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.8. Crisis and non-crisis periods

Variables	Expected sign	OLS		Tobit		GLM	
		DM3	*DM5*	*DM3*	*DM5*	*DM3*	*DM5*
		(I)	(II)	(III)	(IV)	(V)	(VI)
$ASPLIT_{t-1} \times CRISIS_{t-1}$	+	0.009	0.020**	0.009	0.020**	0.051	0.081**
		(1.46)	(2.27)	(1.26)	(2.04)	(1.50)	(2.28)
$ASPLIT_{t-1} \times (1- CRISIS_{t-1})$	+	0.006**	0.007*	0.007**	0.008*	0.034**	0.029*
		(2.16)	(1.85)	(2.06)	(1.83)	(2.13)	(1.88)
$TANG_{t-1}$	+	0.055**	0.067*	0.067**	0.083**	0.311**	0.278*
		(2.07)	(1.75)	(2.35)	(2.02)	(2.06)	(1.77)
FS_{t-1}	+	-0.005	0.011	-0.008	0.015**	-0.024	0.044
		(-0.92)	(1.64)	(-1.42)	(2.11)	(-0.89)	(1.64)
MTB_{t-1}	-	-0.006	0.010	-0.006	0.011	-0.029	0.040
		(-0.61)	(0.78)	(-0.51)	(0.81)	(-0.53)	(0.79)
$PROFIT_{t-1}$	-	0.116	-0.063	0.124	-0.057	0.633	-0.262
		(1.32)	(-0.54)	(1.27)	(-0.44)	(1.31)	(-0.55)
RD_{t-1}	-	0.035	0.066	0.058	0.039	0.241	0.273
		(0.19)	(0.32)	(0.29)	(0.16)	(0.27)	(0.33)
EI_{t-1}	+	0.019***	0.022***	0.020***	0.023***	0.100***	0.091***
		(3.19)	(2.85)	(3.00)	(2.67)	(3.29)	(2.86)
AGE_{t-1}	+	-0.005	0.003	-0.008	0.001	-0.030	0.012
		(-0.87)	(0.37)	(-1.33)	(0.15)	(-0.94)	(0.37)
$INDDM_{t-1}$	+	0.096***	0.085***	0.094***	0.094***	0.505***	0.348***
		(4.82)	(3.13)	(4.37)	(3.12)	(4.85)	(3.15)
Constant		0.177***	0.191***	0.186***	0.154**	-1.344***	-2.185***
		(3.72)	(3.00)	(3.66)	(2.25)	(-5.10)	(-8.34)
ΔCOEF		-0.003	-0.013	-0.002	-0.012	-0.017	-0.052
		(0.20)	(2.13)	(0.09)	(1.61)	(0.22)	(2.12)
Prob > F (χ^2)		0.656	0.145	0.764	0.205	0.636	0.145
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		884	884	884	884	884	884

Note: Table 4.8 reports the results for Eq. (4.1) with with two interaction term, $ASPLIT_{t-1} \times CRISIS_{t-1}$ and $ASPLIT_{t-1} \times (1- CRISIS_{-1})$. The key variables of interest are $ASPLIT_{t-1} \times CRISIS_{t-1}$ and $ASPLIT_{t-1} \times (1- CRISIS_{t-1})$, where $CRISIS_{t-1}$ is a dummy that identifies the crisis period (2007 – 2009). The dependent variables DM3 (DM5) are the ratio of long-term debt maturing in more than 3 (5) years over total debt. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include rating level dummies and Year*Industry fixed effects. The tests of the differences between two interaction terms are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (For ΔCOEF, F-test in Column (I) to (VI) and χ^2-test for Column (V) and (VI)). Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.9. Reverse causality: the impact of debt maturity on future split ratings

Variables	*SPLIT_DUM*				*ASPLIT1*			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$DM3_{t-1}$	-0.011				0.018			
	(-0.11)				(0.21)			
$DM5_{t-1}$		0.069				0.074		
		(0.83)				(1.09)		
$\Delta DM3_{t-1}$			0.004				0.022	
			(0.05)				(0.32)	
$\Delta DM5_{t-1}$				0.029				0.059
				(0.50)				(1.39)
MTB_{t-1}	-0.052	-0.050	-0.026	-0.027	-0.032	-0.031	-0.025	-0.026
	(-1.01)	(-0.96)	(-0.47)	(-0.47)	(-0.68)	(-0.65)	(-0.50)	(-0.51)
$IDIO_{t-1}$	0.018***	0.019***	0.022***	0.022***	0.007**	0.007**	0.008**	0.008**
	(3.40)	(3.42)	(3.60)	(3.61)	(2.03)	(2.11)	(1.98)	(2.09)
MTB_{t-1}	-0.007	-0.006	0.019	0.019	-0.052*	-0.051*	-0.019	-0.019
	(-0.18)	(-0.14)	(0.44)	(0.43)	(-1.74)	(-1.72)	(-0.59)	(-0.60)
$BETA_{t-1}$	-0.064**	-0.063**	-0.066**	-0.066**	-0.081***	-0.082***	-0.083***	-0.084***
	(-2.05)	(-2.05)	(-1.99)	(-1.99)	(-3.03)	(-3.05)	(-2.88)	(-2.89)
FS_{t-1}	-0.091	-0.099	-0.084	-0.084	-0.066	-0.071	-0.036	-0.036
	(-0.56)	(-0.61)	(-0.49)	(-0.49)	(-0.47)	(-0.51)	(-0.24)	(-0.24)
$TANG_{t-1}$	2.162**	2.171**	2.240*	2.244*	2.685***	2.686***	2.978***	2.974***
	(2.09)	(2.10)	(1.94)	(1.94)	(3.09)	(3.09)	(3.13)	(3.12)
RD_{t-1}	-0.107	-0.122	0.002	-0.000	0.280	0.266	0.353	0.345
	(-0.29)	(-0.32)	(0.01)	(-0.00)	(0.85)	(0.81)	(1.00)	(0.98)
$CASH_{t-1}$	-0.052	-0.050	-0.026	-0.027	-0.032	-0.031	-0.025	-0.026
	(-1.01)	(-0.96)	(-0.47)	(-0.47)	(-0.68)	(-0.65)	(-0.50)	(-0.51)
Constant	-1.169*	-1.225*	-1.106*	-1.110*	-0.749**	-0.773***	-7.060***	-7.032***
	(-1.82)	(-1.92)	(-1.68)	(-1.69)	(-2.00)	(-5.72)	(-19.97)	(-19.79)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,335	6,335	5,474	5,474	6,416	6,416	5,522	5,522

Note: Table 4.9 reports the results of reverse causality using the probit model in columns (I) to (IV) and ordered probit model in columns (V) to (VIII). The dependent variables are *SPLIT_DUM*, a dummy variable identifying split-rated firms at year *t*, and *ASPLIT*, the absolute split ratings at year *t*. The main independent variables are the lagged debt maturity ($DM3_{t-1}$ and $DM5_{t-1}$) and the lagged first difference of debt maturity ($\Delta DM3_{t-1}$ and $\Delta DM5_{t-1}$). The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.10. Matching quality tests for NN matching without replacement and the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched / Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|
$IDIO_{t-1}$	U	9.6755	7.9108	32.1		9.32	0.000
	M	7.9424	8.0295	-1.6	95.1	-0.5	0.614
$D2A_{t-1}$	U	0.47792	0.40187	34.6		10.69	0.000
	M	0.4019	0.41194	-4.6	86.8	-1.1	0.272
$TAXES_{-1}$	U	0.01849	0.0267	-32.5		-10.43	0.000
	M	0.02632	0.02571	2.4	92.6	0.63	0.526
$CASH_{-1}$	U	0.08176	0.09315	-12		-4	0.000
	M	0.09222	0.0903	2	83.1	0.5	0.620
FS_{t-1}	U	8.3827	8.8571	-35		-11.18	0.000
	M	8.7494	8.7716	-1.6	95.3	-0.42	0.675
MTB_{t-1}	U	1.2061	1.3616	-22.1		-7.29	0.000
	M	1.3736	1.3401	4.7	78.5	1.08	0.280

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
DM3	Unmatched	0.749	0.718	0.031	0.008	4.04***
	ATT	0.742	0.723	0.019	0.010	1.98**
DM5	Unmatched	0.538	0.526	0.012	0.009	1.31
	ATT	0.551	0.528	0.023	0.012	2.00**

Panel C. Pseudo R^2 test

Sample	Ps R^2	LR chi^2	p>chi^2	MeanBias	MedBias	B	R	%Var
Unmatched	0.112	716.48	0	6.4	3.8	84.7	0.92	67
Matched	0.012	42.04	1	2	1.8	26.2	0.9	50

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the *$SPLIT\_DUM_{t-1}$* variable, which equals one if firms are split rated at time *t – 1* and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), idiosyncratic risk (*IDIO*), leverage (*D2A*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R^2 and the joint significance tests.

Table 4.11. Regressions using a propensity score matched sample (NN matching without replacement and with the caliper of 0.01)

Variables	Probit	OLS (PSM)		Tobit (PSM)		GLM (PSM)	
		DM3	*DM5*	*DM3*	*DM5*	*DM3*	*DM5*
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
$ASPLIT_{t-1}$		0.011**	0.013**	0.011**	0.013**	0.059**	0.055**
		(2.52)	(2.52)	(2.39)	(2.37)	(2.56)	(2.57)
$TANG_{t-1}$		0.052	0.017	0.067*	0.025	0.302	0.072
		(1.46)	(0.34)	(1.79)	(0.49)	(1.52)	(0.35)
FS_{t-1}	-0.001	-0.012	-0.002	-0.015**	-0.001	-0.065	-0.010
	(-0.05)	(-1.63)	(-0.26)	(-1.97)	(-0.13)	(-1.64)	(-0.27)
MTB_{t-1}	-0.017	-0.022	-0.029*	-0.020	-0.029*	-0.105	-0.119*
	(-0.47)	(-1.55)	(-1.75)	(-1.32)	(-1.67)	(-1.53)	(-1.81)
$PROFIT_{t-1}$		0.104	0.128	0.100	0.138	0.531	0.536
		(0.75)	(0.74)	(0.65)	(0.74)	(0.70)	(0.76)
RD_{t-1}		-0.270	-0.171	-0.289	-0.237	-1.093	-0.694
		(-0.95)	(-0.63)	(-0.94)	(-0.77)	(-0.87)	(-0.63)
EI_{t-1}		0.006	0.017	0.006	0.017	0.027	0.071
		(0.62)	(1.50)	(0.62)	(1.39)	(0.62)	(1.55)
AGE_{t-1}		-0.009	-0.003	-0.012*	-0.005	-0.049	-0.011
		(-1.30)	(-0.32)	(-1.71)	(-0.54)	(-1.31)	(-0.31)
$INDDM_{t-1}$		0.100***	0.090**	0.099***	0.099***	0.522***	0.374***
		(3.71)	(2.55)	(3.48)	(2.63)	(3.77)	(2.59)
$IDIO_{t-1}$	0.020***						
	(3.67)						
$TAXES_{-1}$	-4.164***						
	(-4.37)						
$CASH_{-1}$	0.068						
	(0.28)						
$D2A_{t-1}$	0.508***						
	(5.05)						
Constant	0.718***	1.082***	1.075***	1.228***	1.206***	4.801***	4.687***
	(105.44)	(11.97)	(10.38)	(8.78)	(6.74)	(5.95)	(5.59)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,294	2,478	2,478	2,478	2,478	2,478	2,478
Wald χ^2	716.48***						
Adjusted R^2		0.098	0.071				
Pseudo R^2	0.112			0.477	0.183		

Note: Table 4.11 reports the results of the probit regression used to calculate propensity scores (Column (I)) and the main regression using Eq (4.1) and a propensity score matched sample (Column (II) to (VII)). The key variables of interest are $ASPLIT_{t-1}$ except for Column (I). The dependent variables are *DM3* (*DM5*) except for Column (I), where the dependent variable is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), the median industry debt maturity (*INDDM*), idiosyncratic risk (*IDIO*), leverage (*D2A*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 4.1 for definitions. The regressions include rating level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.12. Matching quality tests for NN matching with replacement and the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|
D2A$_{t-1}$	U	0.477	0.403	33.8		10.63	0.000
	M	0.474	0.480	-2.6	92.3	-1.27	0.204
CASH$_{-1}$	U	0.081	0.092	-11.2		-3.81	0.000
	M	0.081	0.082	-0.4	96.7	-0.19	0.850
FS$_{t-1}$	U	8.402	8.882	-35.2		-11.49	0.000
	M	8.412	8.389	1.7	95.3	0.86	0.388
MTB$_{t-1}$	U	1.200	1.365	-23.4		-7.87	0.000
	M	1.200	1.201	-0.1	99.7	-0.03	0.972
TANG$_{t-1}$	U	0.369	0.356	5.1		1.67	0.095
	M	0.369	0.361	2.9	42.4	1.50	0.132

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
DM3	Unmatched	0.750	0.720	0.030	0.007	3.99***
	ATT	0.750	0.733	0.017	0.013	1.34
DM5	Unmatched	0.541	0.529	0.012	0.009	1.3
	ATT	0.541	0.516	0.024	0.015	1.63**

Panel C. Pseudo R^2 test

Sample	Ps R^2	LR chi^2	p>chi^2	MeanBias	MedBias	B	R	%Var
Unmatched	0.104	684.06	0	5.8	3.7	81.2	0.9	80
Matched	0.027	126.67	0.132	2.8	2.4	38.6*	0.99	80

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the *SPLIT_DUM*$_{t-1}$ variable, which equals one if firms are split rated at time $t-1$ and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R^2 and the joint significance tests.

Table 4.13. Regressions using a propensity score matched sample (NN matching with replacement and the caliper of 0.01)

Variables	Probit	OLS (PMS)		Tobit (PMS)		GLM (PMS)	
		DM3	*DM5*	*DM3*	*DM5*	*DM3*	*DM5*
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
$ASPLIT_{t-1}$		0.011**	0.013***	0.012**	0.014**	0.057**	0.053***
		(2.38)	(2.66)	(2.29)	(2.46)	(2.37)	(2.65)
$TANG_{t-1}$	0.176*	0.028	0.007	0.037	0.013	0.165	0.027
	(-1.69)	(0.74)	(0.14)	(0.90)	(0.24)	(0.79)	(0.13)
FS_{t-1}	-0.005	-0.010*	0.004	-0.014**	0.004	-0.056*	0.016
	(-0.22)	(-1.70)	(0.47)	(-2.12)	(0.52)	(-1.68)	(0.48)
MTB_{t-1}	-0.098***	-0.008	0.011	-0.010	0.012	-0.044	0.044
	(-2.97)	(-0.70)	(0.70)	(-0.74)	(0.71)	(-0.69)	(0.69)
$PROFIT_{t-1}$		0.257**	0.131	0.301**	0.156	1.406**	0.552
		(2.08)	(0.86)	(2.14)	(0.90)	(2.05)	(0.86)
RD_{t-1}		-0.384	-0.119	-0.437	-0.259	-1.491	-0.506
		(-0.83)	(-0.33)	(-0.79)	(-0.54)	(-0.75)	(-0.33)
EI_{t-1}		0.012	0.022*	0.009	0.021	0.062	0.095*
		(1.21)	(1.81)	(0.82)	(1.49)	(1.22)	(1.83)
AGE_{t-1}		-0.003	0.005	-0.005	0.005	-0.019	0.021
		(-0.33)	(0.57)	(-0.57)	(0.51)	(-0.38)	(0.55)
$INDDM_{t-1}$		0.131***	0.114***	0.129***	0.119***	0.705***	0.473***
		(4.78)	(3.33)	(4.26)	(3.13)	(4.93)	(3.29)
$CASH_{-1}$	0.247						
	(1.01)						
$D2A_{t-1}$	0.569***						
	(5.75)						
Constant	0.718***	0.826***	0.654***	1.016***	0.813***	1.721*	0.829
	(105.44)	(7.19)	(4.80)	(5.13)	(3.60)	(1.76)	(1.00)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,506	10,266	10,266	10,266	10,266	10,266	10,266
Wald χ^2	684.06***						
Adjusted R^2		0.137	0.117				
Pseudo R^2	0.104			0.388	0.165		

Note: Table 4.13 reports the results of the probit regression used to calculate propensity scores (Column (I)) and the main regression using Eq 4.23 and a propensity score matched sample using NN matching with replacement (Column (II) to (VII)). The key variables of interest are $ASPLIT_{t-1}$ except for Column (I). The dependent variables are *DM3* (*DM5*) except for Column (I), where the dependent variable is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t - 1$ and zero otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), the median industry debt maturity (*INDDM*), idiosyncratic risk (*IDIO*), leverage (*D2A*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 4.1 for definitions. The regressions include rating level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.14. Superior S&P versus superior Moody's ratings and debt maturity

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	*DM5* (II)	*DM3* (III)	*DM5* (IV)	*DM3* (V)	*DM5* (VI)
SUP_MOODY_{t-1}	+	-0.022*	-0.029**	-0.025**	-0.033**	-0.117**	-0.119**
		(-1.96)	(-2.12)	(-2.11)	(-2.27)	(-2.06)	(-2.15)
$SUP\_S\&P_{t-1}$	+	0.024***	0.028**	0.027***	0.031**	0.134***	0.116**
		(2.74)	(2.47)	(2.83)	(2.51)	(2.78)	(2.50)
$TANG_{t-1}$	+	0.056**	0.068*	0.068**	0.084**	0.319**	0.283*
		(2.11)	(1.77)	(2.40)	(2.05)	(2.12)	(1.80)
FS_{t-1}	+	-0.005	0.010	-0.008	0.014**	-0.026	0.043
		(-0.98)	(1.60)	(-1.49)	(2.08)	(-0.95)	(1.60)
MTB_{t-1}	-	-0.006	0.010	-0.006	0.011	-0.028	0.042
		(-0.60)	(0.82)	(-0.50)	(0.85)	(-0.51)	(0.83)
$PROFIT_{t-1}$	-	0.101	-0.082	0.110	-0.077	0.558	-0.344
		(1.17)	(-0.71)	(1.13)	(-0.61)	(1.17)	(-0.73)
RD_{t-1}	-	0.043	0.080	0.064	0.051	0.281	0.331
		(0.24)	(0.39)	(0.33)	(0.22)	(0.33)	(0.40)
EI_{t-1}	+	0.020***	0.023***	0.021***	0.024***	0.103***	0.094***
		(3.31)	(2.97)	(3.13)	(2.79)	(3.42)	(2.99)
AGE_{t-1}	+	-0.004	0.003	-0.008	0.002	-0.027	0.014
		(-0.79)	(0.44)	(-1.25)	(0.23)	(-0.86)	(0.44)
$INDDM_{t-1}$	+	0.096***	0.086***	0.094***	0.094***	0.508***	0.349***
		(4.81)	(3.12)	(4.37)	(3.11)	(4.86)	(3.13)
Constant		0.185***	0.199***	0.192***	0.161**	-1.312***	-2.153***
		(3.96)	(3.18)	(3.87)	(2.39)	(-5.11)	(-8.36)
ΔCOEF		0.046***	0.057***	0.052***	0.064***	0.251***	0.235***
		(16.81)	(16.53)	(19.27)	(17.88)	(18.46)	(17.01)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		844	844	844	844	844	844

Note: Table 4.14 reports the results of Eq. (4.1) that examines the impact of split ratings with superior Moody's ratings or superior S&P ratings on debt maturity ratio using OLS and Tobit modelling approaches. The dependent variables *DM3*(*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt. The main independent variables are SUP_MOODY_{t-1} and $SUP\_S\&P_{t-1}$, where SUP_MOODY_{t-1} ($SUP\_S\&P_{t-1}$) is dummy variable equals to 1 if Moody's (S&P) rating is higher than S&P (Moody's). The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. The tests of the differences between two key independent variables are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (F-test or χ-test for ΔCOEF). Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * denote significance the 1%, 5%, 10% levels, respectively.

Table 4.15. Summary of the key findings of Chapter 4.

Research questions	Equations, hypotheses and tables	Findings
What is the impact of split ratings on firms' debt maturity decisions?	Hypothesis 1 Equation (4.1) Table 4.5	Split rated firms on average have a higher level of long-term debt than non-split rated firms with similar credit risk. Firms with one-notch split have about 2.1% higher long-term debt maturity than their non-split rated peers. This suggests that split ratings are indeed a signal of information asymmetry and that firms with a greater information asymmetry problem rely more on long-term debt.
Is the impact of superior ratings from Moody's on firms' debt maturity choices different from the impact of superior ratings from S&P?	Hypothesis 2 Equation (4.2) Table 4.14	Firms with superior Moody's ratings have a significantly lower level of debt maturity compared to firms with superior S&P ratings, suggesting that firms with inferior Moody's ratings are more likely to have negative private information about their credit risk.
Cross-sectional tests	Small vs large firms, Table 4.6 Investment-grade vs speculative-grade firms, Table 4.7 Crisis vs non-crisis periods, Table 4.8	The effect of split ratings on firms' level of debt maturity is predominantly associated with large firms and firms with speculative ratings. The effect of split ratings on firms' level of long-term debt is stronger during the non-crisis period.
Endogeneity investigation	PSM with various matching methods Tables 4.10, 4.11, 4.12, 4.13, 4.B.1, 4.B.2, 4.B.3, 4.B.4, 4.B.5 and 4.B.6.	The results of PSM methods are very similar to the baseline results. Thus, the main results are unlikely to be affected by potential endogeneity issues. By the nature of the matching methods, PSM also helps separate the effect of information asymmetry arising from split ratings from other sources of information asymmetry.
Additional robustness tests	Different definitions of split ratings, Tables 4.B.7, 4.B.8, and 4.B.9 Excluding missing accounting variables, Tables 4.B.10 and 4.B.11 Excluding financial firms and/or utility firms, Tables 4.B.12, 4.B.13 and 4.B.14	The results and inference from various robustness tests are similar to the baseline results.

Appendix 4.A: Compustat variable definitions

Compustat item	Definition
ajex	Adjustment factor (cumulative) by ex-date, a ratio which enables you to adjust per-share data (price, earnings per share, dividends per share), as well as share data (shares outstanding and shares traded) for all stock splits and stock dividends that occur subsequent to the end of a given period.
at	Total assets, the total assets/liabilities of a company at a point in time.
ceq	Total common equity, this item represents the common shareholders' interest in the company.
che	Cash and short-term investment, cash and all securities readily transferable to cash as listed in the current asset section.
csho	Common shares outstanding, represents the net number of all common shares outstanding at year-end for the annual file, and as of the Balance Sheet date for the quarterly file excluding treasury shares and scrip.
dclo	Debt – capitalized lease obligations, represents the debt obligation a company incurs when capitalizing leases.
dd	Debt debentures represents long-term debt containing a promise to pay a specific amount of money on a fixed date (usually more than 10 years after issuance – and with a promise to pay interest on stated dates).
dd2 to dd5	Debt - maturing in 2nd, 3rd, 4th, and 5th years, the dollar amount of long-term debt that matures in the second, third, fourth, and fifth years from the Balance Sheet.
dlc	Debt in current liabilities represents the total amount of short-term notes and the current portion of long-term debt that is due in one year.
dltt	Total long-term debt represents debt obligations due more than one year from the company's Balance Sheet date or due after the current operating cycle.
dn	Debt – notes, long-term debt possibly secured by the pledge of property or securities owned by the company.
lt	Total liabilities, current liabilities plus long-term debt plus other liabilities plus deferred taxes and investment tax credit plus minority interest.
oibdp	Operating income before depreciation represents Sales - Net (*sale*) minus cost of goods sold (*cogs*) and selling, general, and administrative expenses (*xsga*) before deducting depreciation, depletion and amortization (*dpact*).
ppent	Total (gross) property, plant and equipment represents the cost of fixed property of a company used in the production of revenue before adjustments for accumulated depreciation, depletion, and amortization.
prccm	Price close monthly.
prcc_f	Price close at the end of the fiscal year.
pstkl	Preferred stock – liquidating value, the total dollar value of the net number of preferred shares outstanding in the event of involuntary liquidation.
sale	Net sales, gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers.
trfm	Monthly total return factor.
txditc	Deferred taxes and investment tax credit, the accumulated differences between income expense for financial statements and tax forms due to timing differences and investment tax credit.
txt	Total income taxes, all income taxes imposed by federal, state and foreign governments.
xrd	Research and development expense represents all costs that relate to the development of new products or services.

Note: The table provides the definitions of all Compustat items used.

Appendix 4.B: Additional robustness tests

Table 4.B.1. Matching quality tests for radius matching with the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|
$D2A_{t-1}$	U	0.477	0.403	33.8		10.63	0.000
	M	0.474	0.468	3	91.3	1.46	0.143
$CASH_{-1}$	U	0.081	0.092	-11.2		-3.81	0.000
	M	0.081	0.083	-2.2	80.6	-1.11	0.267
FS_{t-1}	U	8.402	8.882	-35.2		-11.49	0.000
	M	8.412	8.424	-0.9	97.6	-0.44	0.662
MTB_{t-1}	U	1.200	1.365	-23.4		-7.87	0.000
	M	1.200	1.206	-0.9	96.3	-0.48	0.634
$TANG_{t-1}$	U	0.369	0.356	5.1		1.67	0.095
	M	0.369	0.365	1.5	70.5	0.77	0.444

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
DM3	Unmatched	0.750	0.720	0.030	0.007	3.99
	ATT	0.751	0.730	0.021	0.010	1.99
DM5	Unmatched	0.541	0.529	0.012	0.009	1.3
	ATT	0.541	0.523	0.018	0.012	1.43

Panel C. Pseudo R^2 test

Sample	Ps R^2	LR chi^2	p>chi^2	MeanBias	MedBias	B	R	%Var
Unmatched	0.104	684.06	0	5.8	3.7	81.2	0.9	80
Matched	0.031	101.09	0.668	3	2.2	41.5	1.12	40

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the $SPLIT\_DUM_{t-1}$ variable, which equals one if firms are split rated at time $t-1$ and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*), book value of cash over total asset (*CASH*), and tangibility (*TANG*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R^2 and the joint significance tests.

Table 4.B.2. **Regressions using a propensity score matched sample (radius matching with the caliper of 0.01)**

Variables	Probit	OLS (PMS)		Tobit (PMS)		GLM (PMS)	
		DM3	*DM5*	*DM3*	*DM5*	*DM3*	*DM5*
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
$ASPLIT_{t-1}$		0.010**	0.010**	0.011**	0.011**	0.055**	0.042**
		(2.37)	(2.17)	(2.31)	(2.05)	(2.37)	(2.18)
$TANG_{t-1}$	0.176*	0.020	-0.003	0.027	0.001	0.113	-0.012
	(-1.69)	(0.54)	(-0.06)	(0.67)	(0.01)	(0.55)	(-0.06)
FS_{t-1}	-0.005	-0.013**	0.001	-0.016**	0.002	-0.068**	0.004
	(-0.22)	(-2.04)	(0.12)	(-2.43)	(0.21)	(-2.04)	(0.12)
MTB_{t-1}	-0.098***	-0.017	-0.001	-0.017	-0.002	-0.089	-0.005
	(-2.97)	(-1.39)	(-0.07)	(-1.28)	(-0.10)	(-1.40)	(-0.08)
$PROFIT_{t-1}$		0.243**	0.155	0.269*	0.190	1.330**	0.647
		(1.98)	(1.09)	(1.93)	(1.18)	(1.97)	(1.09)
RD_{t-1}		-0.407	-0.184	-0.454	-0.324	-1.624	-0.770
		(-0.88)	(-0.52)	(-0.83)	(-0.68)	(-0.82)	(-0.52)
EI_{t-1}		0.020**	0.033***	0.018*	0.032**	0.099**	0.138***
		(2.24)	(2.85)	(1.81)	(2.49)	(2.27)	(2.86)
AGE_{t-1}		-0.003	0.002	-0.005	0.002	-0.017	0.009
		(-0.34)	(0.25)	(-0.59)	(0.18)	(-0.39)	(0.23)
$INDDM_{t-1}$		0.124***	0.104***	0.123***	0.111***	0.663***	0.429***
		(4.60)	(2.98)	(4.18)	(2.88)	(4.72)	(2.97)
$CASH_{-1}$	0.247						
	(1.01)						
$D2A_{t-1}$	0.569***						
	(5.75)						
Constant	0.792***	0.584***	0.897***	0.657**	1.337	0.353	0.792***
	(5.54)	(2.84)	(4.28)	(2.22)	(1.54)	(0.38)	(5.54)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,085	6,085	6,085	6,085	6,085	6,085	6,085
Wald χ^2	684.06***						
Adjusted R^2		0.117	0.089				
Pseudo R^2	0.104			0.347	0.137		

Note: Table 4.B.2 reports the results of the probit regression used to calculate propensity scores (Column (I)) and the main regression using Eq 4.23 and a propensity score matched sample using radius matching (Column (II) to (VII)). The key variables of interest are $ASPLIT_{t-1}$ except for Column (I). The dependent variables are *DM3* (*DM5*) except for Column (I), where the dependent variable is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t - 1$ and zero otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), the median industry debt maturity (*INDDM*), idiosyncratic risk (*IDIO*), leverage (*D2A*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 1 for definitions. The regressions include rating level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.3. Matching quality tests for kernel matching with the bandwidth of 0.06.

Panel A. Standardised bias test

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|
$TAXES_{t-1}$	U	0.019	0.027	-32.2		-10.35	0.000
	M	0.019	0.018	2.8	91.4	1.37	0.170
$CASH_{-1}$	U	0.082	0.093	-11.8		-3.96	0.000
	M	0.082	0.085	-3.2	73.2	-1.59	0.113
FS_{t-1}	U	8.385	8.859	-35		-11.19	0.000
	M	8.385	8.400	-1.1	96.9	-0.54	0.587
MTB_{t-1}	U	1.207	1.364	-22.1		-7.33	0.000
	M	1.207	1.205	0.3	98.8	0.15	0.882
$TANG_{t-1}$	U	0.367	0.351	6.2		2.03	0.043
	M	0.367	0.361	2.2	64.8	1.11	0.269

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
DM3	Unmatched	0.749	0.718	0.031	0.008	4.03
	ATT	0.749	0.726	0.023	0.010	2.33
DM5	Unmatched	0.539	0.526	0.013	0.009	1.35
	ATT	0.539	0.517	0.022	0.011	1.91

Panel C. Pseudo R^2 test

Sample	Ps R^2	LR chi^2	p>chi^2	MeanBias	MedBias	B	R	%Var
Unmatched	0.106	676.12	0	5.9	3.6	81.8*	0.84	60
Matched	0.019	105.49	0.655	2.5	2.5	32.7*	1.31	60

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the $SPLIT\_DUM_{t-1}$ variable, which equals one if firms are split rated at time $t-1$ and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), taxes over total assets ratio (*TAXES*), book value of cash over total asset (*CASH*), and tangibility (*TANG*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R^2 and the joint significance tests.

Table 4.B.4. Regressions using a propensity score matched sample (kernel matching)

Variables	Probit	OLS (PMS)		Tobit (PMS)		GLM (PMS)	
		DM3	*DM5*	*DM3*	*DM5*	*DM3*	*DM5*
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
$ASPLIT_{t-1}$		0.010**	0.011**	0.011**	0.012**	0.053**	0.046**
		(2.31)	(2.34)	(2.18)	(2.19)	(2.31)	(2.36)
$TANG_{t-1}$	-0.047	0.008	-0.025	0.013	-0.024	0.046	-0.107
	(-1.69)	(0.24)	(-0.54)	(0.34)	(-0.46)	(0.24)	(-0.54)
FS_{t-1}	0.012	-0.012*	0.002	-0.017**	0.002	-0.066*	0.007
	(-0.22)	(-1.93)	(0.20)	(-2.40)	(0.24)	(-1.94)	(0.20)
MTB_{t-1}	-0.011	-0.011	-0.001	-0.009	0.000	-0.054	-0.004
	(-2.97)	(-0.83)	(-0.04)	(-0.65)	(0.02)	(-0.82)	(-0.06)
$PROFIT_{t-1}$		0.193	0.063	0.198	0.078	1.052	0.272
		(1.57)	(0.41)	(1.39)	(0.45)	(1.57)	(0.43)
RD_{t-1}		-0.601	-0.381	-0.681	-0.593	-2.497	-1.626
		(-1.35)	(-1.19)	(-1.28)	(-1.32)	(-1.33)	(-1.17)
EI_{t-1}		0.024**	0.031***	0.024**	0.031**	0.121**	0.133***
		(2.31)	(2.83)	(2.03)	(2.56)	(2.36)	(2.86)
AGE_{t-1}		-0.006	0.001	-0.008	0.001	-0.037	0.002
		(-0.90)	(0.08)	(-1.03)	(0.07)	(-0.95)	(0.06)
$INDDM_{t-1}$		0.134***	0.116***	0.138***	0.128***	0.717***	0.483***
		(4.95)	(3.33)	(4.61)	(3.32)	(5.10)	(3.33)
$CASH_{-1}$	0.247						
	(1.01)						
$TAXES_{-1}$	-4.526***						
	(-4.85)						
Constant	-0.734	0.795***	0.544***	0.880***	0.577***	1.360**	0.172
	(-1.13)	(7.33)	(4.23)	(6.17)	(3.37)	(2.16)	(0.31)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,326	6,325	6,325	6,325	6,325	6,325	6,325
Wald $\chi 2$	676.12***						
Adjusted R^2		0.129	0.097				
Pseudo R^2	0.106			0.334	0.141		

Note: Table 4.B.4 reports the results of the probit regression used to calculate propensity scores (Column (I)) and the main regression using Eq 4.23 and a propensity score matched sample using kernel matching (Column (II) to (VII)). The key variables of interest are $ASPLIT_{t-1}$ except for Column (I). The dependent variables are *DM3* (*DM5*) except for Column (I), where the dependent variable is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), the median industry debt maturity (*INDDM*), idiosyncratic risk (*IDIO*), leverage (*D2A*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 1 for definitions. The regressions include rating level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.5. Matching quality tests for Mahalanobis matching.

Panel A. Standardised bias test

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
TAXES$_{-1}$	U	0.018	0.027	-33.2		-10.67	0.000
	M	0.018	0.019	-1.3	96	-0.84	0.399
D2A$_{t-1}$	U	0.479	0.402	34.1		10.40	0.000
	M	0.464	0.463	0.6	98.3	0.29	0.772
CASH$_{-1}$	U	0.366	0.351	5.9		1.91	0.056
	M	0.378	0.379	-0.5	91.2	-0.19	0.848
FS$_{t-1}$	U	0.082	0.094	-11.6		-3.88	0.000
	M	0.056	0.056	0.6	95	0.34	0.734
MTB$_{t-1}$	U	8.365	8.857	-36.3		-11.62	0.000
	M	8.534	8.557	-1.7	95.4	-0.70	0.486
TANG$_{t-1}$	U	1.2056	1.3644	-22.4		-7.44	0
	M	1.0601	1.0617	-0.2	99	-0.14	0.891

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
DM3	Unmatched	0.750	0.718	0.032	0.008	4.21***
	ATT	0.753	0.736	0.017	0.013	1.33
DM5	Unmatched	0.538	0.526	0.012	0.009	1.29
	ATT	0.547	0.515	0.032	0.013	2.55***

Panel C. Pseudo R^2 test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.043	278.49	0	23.9	27.8	52.4	0.96	67
Matched	0.000	1.46	0.962	0.8	0.6	3.2	1.03	0

Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the *SPLIT_DUM*$_{t-1}$ variable, which equals one if firms are split rated at time *t – 1* and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), leverage (*D2A*), book value of cash over total asset (*CASH*), and tangibility (*TANG*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R^2 and the joint significance tests.

Table 4.B.6. Regressions using a propensity score matched sample (Mahalanobis matching)

	OLS (PMS)		Tobit (PMS)		GLM (PMS)	
Variables	*DM3*	*DM5*	*DM3*	*DM5*	DM3	DM5
	(I)	(II)	(III)	(IV)	(V)	(VI)
$ASPLIT_{t-1}$	0.008**	0.013***	0.008**	0.013***	0.043**	0.054***
	(2.41)	(2.72)	(2.45)	(2.65)	(2.40)	(2.76)
$TANG_{t-1}$	0.071**	0.091*	0.085**	0.103*	0.395**	0.380*
	(2.05)	(1.71)	(2.35)	(1.94)	(2.08)	(1.76)
FS_{t-1}	-0.016**	0.001	-0.018***	0.002	-0.090***	0.003
	(-2.53)	(0.11)	(-2.90)	(0.25)	(-2.62)	(0.10)
MTB_{t-1}	-0.004	-0.004	0.002	-0.005	-0.003	-0.017
	(-0.22)	(-0.19)	(0.14)	(-0.21)	(-0.03)	(-0.18)
$PROFIT_{t-1}$	-0.154	-0.268	-0.196	-0.263	-0.933	-1.133
	(-1.10)	(-1.32)	(-1.30)	(-1.25)	(-1.17)	(-1.36)
RD_{t-1}	0.187	0.229	0.210	0.229	1.068	0.952
	(0.79)	(0.70)	(0.86)	(0.65)	(0.87)	(0.71)
EI_{t-1}	0.026***	0.023	0.027***	0.023	0.135***	0.094*
	(2.82)	(1.64)	(2.77)	(1.64)	(2.90)	(1.67)
AGE_{t-1}	-0.008	0.006	-0.010	0.005	-0.049	0.024
	(-1.23)	(0.62)	(-1.40)	(0.54)	(-1.25)	(0.64)
$INDDM_{t-1}$	0.008**	0.013***	0.008**	0.013***	0.043**	0.054***
	(2.41)	(2.72)	(2.45)	(2.65)	(2.40)	(2.76)
$CASH_{-1}$						
$D2A_{t-1}$						
Constant	1.270***	1.103***	1.285***	1.098***	4.926***	2.921***
	(15.08)	(7.25)	(14.75)	(7.06)	(10.14)	(4.35)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,744	3,744	3,744	3,744	3,744	3,744
Adjusted R^2	0.115	0.098				
Pseudo R^2			0.347	0.260		

Note: Table 4.B.6 reports the results of the probit regression used to calculate propensity scores (Column (I)) and the main regression using Eq 4.23 and a propensity score matched sample using Mahalanobis matching (Column (II) to (VII)). The key variables of interest are $ASPLIT_{t-1}$ except for Column (I). The dependent variables are *DM3* (*DM5*) except for Column (I), where the dependent variable is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), the median industry debt maturity (*INDDM*), idiosyncratic risk (*IDIO*), leverage (*D2A*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 1 for definitions. The regressions include rating level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 2. ***, **, and * denote significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.7. Split ratings (only below 0.5 split is rounded) and debt maturity

Variables	Expected sign	OLS DM3 (I)	OLS DM5 (II)	Tobit DM3 (III)	Tobit DM5 (IV)	GLM DM3 (V)	GLM DM5 (VI)
$ASPLIT1_{t-1}$	+	0.007**	0.009**	0.007**	0.009**	0.037**	0.037**
		(2.37)	(2.37)	(2.20)	(2.27)	(2.35)	(2.39)
$TANG_{t-1}$	+	0.055**	0.067*	0.067**	0.082**	0.311**	0.277*
		(2.06)	(1.73)	(2.34)	(2.01)	(2.06)	(1.75)
FS_{t-1}	+	-0.005	0.011	-0.008	0.015**	-0.024	0.044*
		(-0.91)	(1.64)	(-1.42)	(2.12)	(-0.88)	(1.65)
MTB_{t-1}	-	-0.006	0.010	-0.006	0.011	-0.029	0.041
		(-0.60)	(0.81)	(-0.51)	(0.83)	(-0.53)	(0.81)
$PROFIT_{t-1}$	-	0.115	-0.064	0.124	-0.058	0.631	-0.267
		(1.32)	(-0.56)	(1.27)	(-0.45)	(1.31)	(-0.57)
RD_{t-1}	-	0.035	0.068	0.058	0.040	0.242	0.278
		(0.19)	(0.33)	(0.29)	(0.17)	(0.27)	(0.33)
EI_{t-1}	+	0.019***	0.022***	0.020***	0.023***	0.100***	0.091***
		(3.19)	(2.85)	(3.00)	(2.67)	(3.30)	(2.87)
AGE_{t-1}	+	-0.005	0.003	-0.008	0.001	-0.030	0.011
		(-0.87)	(0.36)	(-1.33)	(0.14)	(-0.95)	(0.36)
$INDDM_{t-1}$	+	0.096***	0.086***	0.094***	0.094***	0.505***	0.349***
		(4.82)	(3.14)	(4.38)	(3.13)	(4.85)	(3.15)
Constant		0.176***	0.186***	0.185***	0.150**	-1.351***	-2.205***
		(3.69)	(2.92)	(3.64)	(2.18)	(-5.11)	(-8.41)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		884	884	884	884	884	884

Note: Table 4.B.7 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches. The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time t. The main independent variable is the split rating (*ASPLIT1*), which is the absolute average daily rating differences between Moody's and S&P at time $t-1$ and is rounded to 0 for any split below 0.5. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.8. Split ratings (without capping at 4 CCR units) and debt maturity

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	DM5 (II)	DM3 (III)	DM5 (IV)	DM3 (V)	DM5 (VI)
$ASPLIT2_{t-1}$	+	0.004**	0.005**	0.004*	0.005*	0.022*	0.023**
		(1.99)	(2.05)	(1.82)	(1.88)	(1.96)	(2.07)
$TANG_{t-1}$	+	0.056**	0.067*	0.068**	0.083**	0.314**	0.280*
		(2.08)	(1.75)	(2.36)	(2.03)	(2.07)	(1.77)
FS_{t-1}	+	-0.005	0.010	-0.008	0.014**	-0.027	0.042
		(-1.00)	(1.56)	(-1.51)	(2.04)	(-0.97)	(1.57)
MTB_{t-1}	-	-0.006	0.010	-0.006	0.011	-0.029	0.041
		(-0.61)	(0.80)	(-0.51)	(0.83)	(-0.53)	(0.81)
$PROFIT_{t-1}$	-	0.111	-0.070	0.119	-0.064	0.607	-0.290
		(1.27)	(-0.60)	(1.22)	(-0.50)	(1.26)	(-0.61)
RD_{t-1}	-	0.040	0.074	0.064	0.048	0.269	0.305
		(0.22)	(0.36)	(0.32)	(0.20)	(0.30)	(0.37)
EI_{t-1}	+	0.019***	0.022***	0.020***	0.023***	0.100***	0.091***
		(3.18)	(2.84)	(2.99)	(2.67)	(3.29)	(2.86)
AGE_{t-1}	+	-0.005	0.003	-0.008	0.001	-0.030	0.011
		(-0.87)	(0.36)	(-1.32)	(0.15)	(-0.95)	(0.36)
$INDDM_{t-1}$	+	0.096***	0.086***	0.094***	0.094***	0.508***	0.351***
		(4.83)	(3.15)	(4.38)	(3.14)	(4.87)	(3.16)
Constant		0.190***	0.203***	0.199***	0.168**	-1.278***	-2.133***
		(4.02)	(3.25)	(3.96)	(2.49)	(-4.92)	(-8.27)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		884	884	884	884	884	884

Note: Table 4.B.8 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches. The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time t. The main independent variable is the split rating (*ASPLIT2*), which is the rounded absolute average daily rating differences between Moody's and S&P at time $t - 1$ without capping split ratings at 4 CCR unit. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.9. Split ratings (without capping and rounding) and debt maturity

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	DM5 (II)	DM3 (III)	DM5 (IV)	DM3 (V)	DM5 (VI)
ASPLIT3$_{t-1}$	+	0.004**	0.006**	0.004*	0.006*	0.023**	0.024**
		(2.02)	(2.13)	(1.86)	(1.95)	(1.99)	(2.15)
TANG$_{t-1}$	+	0.056**	0.067*	0.068**	0.083**	0.314**	0.280*
		(2.09)	(1.75)	(2.37)	(2.03)	(2.07)	(1.78)
FS$_{t-1}$	+	-0.005	0.010	-0.008	0.014**	-0.027	0.042
		(-1.00)	(1.57)	(-1.51)	(2.04)	(-0.97)	(1.57)
MTB$_{t-1}$	-	-0.006	0.010	-0.006	0.011	-0.029	0.041
		(-0.60)	(0.81)	(-0.51)	(0.83)	(-0.53)	(0.82)
PROFIT$_{t-1}$	-	0.111	-0.070	0.119	-0.064	0.606	-0.291
		(1.27)	(-0.60)	(1.22)	(-0.50)	(1.25)	(-0.61)
RD$_{t-1}$	-	0.040	0.073	0.064	0.047	0.266	0.301
		(0.22)	(0.35)	(0.32)	(0.19)	(0.30)	(0.36)
EI$_{t-1}$	+	0.019***	0.022***	0.020***	0.023***	0.100***	0.091***
		(3.18)	(2.84)	(2.99)	(2.67)	(3.29)	(2.86)
AGE$_{t-1}$	+	-0.005	0.003	-0.008	0.001	-0.030	0.011
		(-0.87)	(0.36)	(-1.33)	(0.14)	(-0.95)	(0.36)
INDDM$_{t-1}$	+	0.096***	0.086***	0.094***	0.094***	0.507***	0.351***
		(4.82)	(3.15)	(4.38)	(3.14)	(4.86)	(3.16)
Constant		0.188***	0.201***	0.197***	0.166**	-1.286***	-2.142***
		(4.00)	(3.21)	(3.94)	(2.45)	(-4.95)	(-8.30)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,630	6,630	6,630	6,630	6,630	6,630
Number of firms		884	884	884	884	884	884

Note: Table 4.B.9 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches. The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time t. The main independent variable is the split rating (*ASPLIT3*), which is the absolute average daily rating differences between Moody's and S&P at time *t – 1* without capping split ratings at 4 CCR unit and rounding up. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.10. Split ratings and debt maturity (relaxing of debt due within 1,2,3,4 and 5 years condition)

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	DM5 (II)	DM3 (III)	DM5 (IV)	DM3 (V)	DM5 (VI)
$ASPLIT_{t-1}$	+	0.006**	0.008**	0.006**	0.008**	0.034**	0.032**
		(2.22)	(2.14)	(2.03)	(2.03)	(2.19)	(2.17)
$TANG_{t-1}$	+	0.052*	0.085**	0.061**	0.098**	0.290*	0.351**
		(1.92)	(2.24)	(2.10)	(2.45)	(1.91)	(2.27)
FS_{t-1}	+	-0.006	0.017***	-0.008	0.022***	-0.029	0.070***
		(-1.07)	(2.62)	(-1.58)	(3.19)	(-1.07)	(2.64)
MTB_{t-1}	-	-0.013	0.003	-0.012	0.004	-0.060	0.011
		(-1.12)	(0.21)	(-0.98)	(0.27)	(-1.07)	(0.21)
$PROFIT_{t-1}$	-	0.139	-0.044	0.138	-0.044	0.745	-0.183
		(1.55)	(-0.38)	(1.41)	(-0.35)	(1.53)	(-0.38)
RD_{t-1}	-	0.114	0.056	0.142	0.024	0.633	0.235
		(0.66)	(0.28)	(0.77)	(0.11)	(0.76)	(0.29)
EI_{t-1}	+	0.017***	0.021**	0.017***	0.021**	0.087***	0.086**
		(2.79)	(2.52)	(2.59)	(2.30)	(2.87)	(2.53)
AGE_{t-1}	+	-0.004	0.004	-0.007	0.003	-0.024	0.018
		(-0.73)	(0.63)	(-1.19)	(0.44)	(-0.79)	(0.64)
$INDDM_{t-1}$	+	0.095***	0.097***	0.094***	0.106***	0.492***	0.398***
		(4.78)	(3.76)	(4.46)	(3.77)	(4.80)	(3.78)
Constant		-0.011	-0.388**	0.001	-0.453**	-2.633***	-5.132***
		(-0.10)	(-2.33)	(0.01)	(-2.44)	(-4.68)	(-7.42)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,063	5,951	6,063	5,951	6,063	5,951
Number of firms		851	844	851	844	851	844

Note: Table 4.B.10 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches. The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time *t* and calculated with the relaxation of the debt due within 1,2,3,4 and 5 years condition. The main independent variable is the split rating (*ASPLIT*), which is the rounded value of the absolute average daily rating differences between Moody's and S&P at time *t-1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.11. Split ratings and debt maturity (relaxing of research and development expenses condition)

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	DM5 (II)	DM3 (III)	DM5 (IV)	DM3 (V)	DM5 (VI)
$ASPLIT_{t-1}$	+	0.013***	0.016***	0.013***	0.017***	0.066***	0.065***
		(2.90)	(2.91)	(2.76)	(2.84)	(2.92)	(2.95)
$TANG_{t-1}$	+	0.016	-0.001	0.012	0.009	0.084	-0.003
		(0.37)	(-0.03)	(0.28)	(0.15)	(0.38)	(-0.02)
FS_{t-1}	+	-0.012	0.007	-0.014*	0.012	-0.059	0.029
		(-1.54)	(0.74)	(-1.72)	(1.14)	(-1.52)	(0.75)
MTB_{t-1}	-	-0.013	0.001	-0.016	0.001	-0.055	0.007
		(-0.86)	(0.08)	(-0.97)	(0.03)	(-0.76)	(0.10)
$PROFIT_{t-1}$	-	-0.020	-0.181	-0.024	-0.208	-0.128	-0.746
		(-0.14)	(-0.98)	(-0.16)	(-1.02)	(-0.18)	(-0.99)
RDN_{t-1}	-	-0.004	0.044	0.042	0.009	0.014	0.178
		(-0.02)	(0.19)	(0.19)	(0.03)	(0.01)	(0.20)
EI_{t-1}	+	0.029***	0.023**	0.029***	0.022*	0.135***	0.097**
		(3.19)	(2.12)	(3.00)	(1.82)	(3.23)	(2.15)
AGE_{t-1}	+	-0.006	0.003	-0.009	0.001	-0.030	0.013
		(-0.62)	(0.31)	(-0.94)	(0.10)	(-0.62)	(0.31)
$INDDM_{t-1}$	+	0.102***	0.077**	0.108***	0.083**	0.526***	0.316**
		(3.86)	(2.30)	(3.91)	(2.30)	(3.94)	(2.33)
Constant		0.612***	0.442***	0.643***	0.398***	0.582	-0.219
		(6.49)	(3.50)	(6.63)	(3.02)	(1.20)	(-0.41)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		3,372	3,372	3,372	3,372	3,372	3,372
Number of firms		454	454	454	454	454	454

Note: Table 4.B.11 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches. The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time *t*. The main independent variable is the split rating (*ASPLIT*), which is the rounded value of the absolute average daily rating differences between Moody's and S&P at time *t-1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RDN*, without setting *xrd* to zero), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.12. Main regression on a sample without financial firms.

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	DM5 (II)	DM3 (III)	DM5 (IV)	DM3 (V)	DM5 (VI)
ASPLIT$_{t-1}$	+	0.007**	0.009**	0.007**	0.009**	0.036**	0.037**
		(2.33)	(2.38)	(2.15)	(2.29)	(2.30)	(2.40)
TANG$_{t-1}$	+	0.058**	0.070*	0.071**	0.085**	0.329**	0.289*
		(2.16)	(1.79)	(2.45)	(2.05)	(2.14)	(1.81)
FS$_{t-1}$	+	-0.005	0.010	-0.008	0.013*	-0.026	0.040
		(-0.95)	(1.49)	(-1.46)	(1.94)	(-0.93)	(1.49)
MTB$_{t-1}$	-	-0.006	0.010	-0.006	0.011	-0.030	0.040
		(-0.60)	(0.78)	(-0.49)	(0.79)	(-0.54)	(0.79)
PROFIT$_{t-1}$	-	0.118	-0.066	0.126	-0.058	0.645	-0.275
		(1.35)	(-0.57)	(1.29)	(-0.46)	(1.33)	(-0.58)
RD$_{t-1}$	-	0.034	0.059	0.057	0.030	0.239	0.242
		(0.19)	(0.28)	(0.28)	(0.13)	(0.27)	(0.29)
EI$_{t-1}$	+	0.020***	0.023***	0.020***	0.024***	0.101***	0.094***
		(3.24)	(2.94)	(3.05)	(2.76)	(3.34)	(2.95)
AGE$_{t-1}$	+	-0.005	0.001	-0.008	-0.001	-0.031	0.003
		(-0.89)	(0.10)	(-1.36)	(-0.13)	(-0.98)	(0.10)
INDDM$_{t-1}$	+	0.094***	0.082***	0.092***	0.090***	0.495***	0.334***
		(4.70)	(2.99)	(4.3)	(2.98)	(4.72)	(3.00)
Constant		0.177***	0.201***	0.186***	0.167**	-1.341***	-2.144***
		(3.65)	(3.13)	(3.60)	(2.43)	(-5.02)	(-8.12)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,555	6,555	6,555	6,555	6,555	6,555
Number of firms		875	875	875	875	875	875

Note: Table 4.B.12 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches with no-financial firms sample (excluding SIC codes 6000-6999). The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time t. The main independent variable is the split rating (*ASPLIT*), which is the rounded value of the absolute average daily rating differences between Moody's and S&P at time *t-1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.13. Main regression on a sample without utility firms.

Variables	Expected sign	OLS		Tobit		GLM	
		DM3 (I)	DM5 (II)	DM3 (III)	DM5 (IV)	DM3 (V)	DM5 (VI)
$ASPLIT_{t-1}$	+	0.007**	0.009**	0.007**	0.009**	0.038**	0.037**
		(2.20)	(2.17)	(2.05)	(2.07)	(2.22)	(2.19)
$TANG_{t-1}$	+	0.059**	0.048	0.074**	0.064	0.338**	0.197
		(2.02)	(1.15)	(2.36)	(1.43)	(2.04)	(1.16)
FS_{t-1}	+	-0.003	0.016**	-0.006	0.022***	-0.017	0.067**
		(-0.52)	(2.16)	(-1.02)	(2.63)	(-0.53)	(2.18)
MTB_{t-1}	-	-0.008	0.010	-0.008	0.011	-0.039	0.040
		(-0.74)	(0.76)	(-0.67)	(0.79)	(-0.68)	(0.76)
$PROFIT_{t-1}$	-	0.121	-0.009	0.126	-0.002	0.646	-0.037
		(1.35)	(-0.08)	(1.25)	(-0.01)	(1.31)	(-0.08)
RD_{t-1}	-	0.042	0.038	0.070	0.004	0.284	0.159
		(0.22)	(0.18)	(0.34)	(0.02)	(0.32)	(0.19)
EI_{t-1}	+	0.021***	0.024***	0.021***	0.024***	0.106***	0.098***
		(3.31)	(2.96)	(3.09)	(2.73)	(3.41)	(2.97)
AGE_{t-1}	+	-0.004	0.000	-0.008	-0.002	-0.027	0.002
		(-0.68)	(0.05)	(-1.10)	(-0.17)	(-0.75)	(0.05)
$INDDM_{t-1}$	+	0.097***	0.089***	0.095***	0.098***	0.511***	0.363***
		(4.77)	(3.20)	(4.27)	(3.17)	(4.80)	(3.21)
Constant		0.147***	0.158**	0.161***	0.118	-1.512***	-2.314***
		(2.60)	(2.13)	(2.66)	(1.46)	(-4.80)	(-7.59)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		5,897	5,897	5,897	5,897	5,897	5,897
Number of firms		802	802	802	802	802	802

Note: Table 4.B.13 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches with no-utility firms sample (excluding SIC codes 4900-4999). The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time t. The main independent variable is the split rating (*ASPLIT*), which is the rounded value of the absolute average daily rating differences between Moody's and S&P at time *t-1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Table 4.B.14. Logit transformation of debt maturity.

Variables	Expected sign	OLS LnDM3 (I)	 LnDM5 (II)
$ASPLIT_{t-1}$	+	0.060**	0.055
		(2.45)	(1.19)
$TANG_{t-1}$	+	0.015	0.700*
		(0.06)	(1.82)
FS_{t-1}	+	-0.159***	0.102
		(-4.04)	(1.51)
MTB_{t-1}	-	0.023	0.046
		(0.27)	(0.29)
$PROFIT_{t-1}$	-	1.044	0.016
		(1.32)	(0.01)
RD_{t-1}	-	0.542	2.203
		(0.41)	(1.10)
EI_{t-1}	+	0.219***	0.250**
		(4.04)	(1.96)
AGE_{t-1}	+	-0.078	-0.035
		(-1.58)	(-0.38)
$INDDM_{t-1}$	+	0.615***	0.852**
		(3.74)	(2.50)
Constant		-1.026***	-2.992***
		(-2.58)	(-4.45)
Year *Industry Interactions		Yes	Yes
Rating Level Dummies		Yes	Yes
Observations		6,059	6,059
Number of firms		849	849

Note: Table 4.B.14 reports the results of Eq. (4.1) using the OLS, Tobit and GLM modelling approaches. The dependent variables *LnDM3* (*LnDM5*) are the logit transformation of the ratio of long-term debt maturing in more than 3 (5) years over total debt at time *t* using Eq. (4.14). The main independent variable is the split rating (*ASPLIT*), which is the rounded value of the absolute average daily rating differences between Moody's and S&P at time *t-1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*), see Table 4.1 for definitions. The regressions include Rating Level dummies and Year*Industry fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Appendix 4.C. Superior Rating Model, Inferior Rating Model and Debt Maturity

Similar to Appendix 3.D, two regression models are used to separate the impact of split ratings (information risk) and credit rating levels (credit risk) on firms' debt maturity.

The first regression model is the superior rating model:

$$DM_{i,t} = \beta_0 + \beta_S ASPLIT_{i,t-1} + \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} SUP\_LEVEL_{i,k,t-1} + \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \tag{4.C.1}$$

In the second model is the inferior rating model:

$$DM_{i,t} = \beta_0 + \beta_I ASPLIT_{i,t-1} + \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} INF\_LEVEL_{i,k,t-1} + \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \tag{4.C.2}$$

The regression results are illustrated in Figure 4.C.1. Since β_S and β_I are both positive, the actual level of debt maturity of split rated firms is above the estimated level of debt maturity of these firms if CRAs had assigned the same inferior or superior rating.

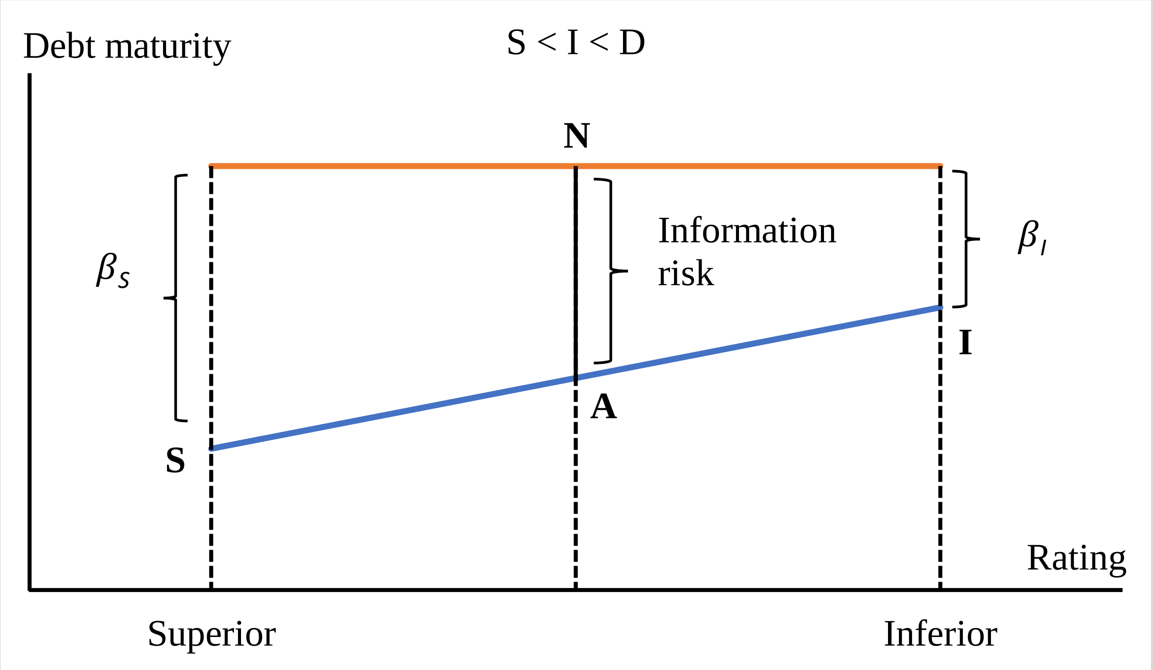

Figure 4.C.1. Illustration of information risk, credit risk and debt maturity
I is the estimated debt maturity level on split rated firms if both CRAs had assigned the same inferior rating level. *S* is the estimated debt maturity level on split rated firms if both CRAs had assigned the same superior rating level. *A* is the average of *I* and *S*. *D* is the actual debt maturity level of the split rated firms. The different between *D* and *A* is the information risk arising from split ratings.

Table 4.C.1 reports the results of the two regression models. In the superior rating model, the coefficient for *ASPLIT* (β_S) is 0.007 for *DM3* (0.009 for *DM5*) and significant, suggesting that an inferior rating significantly increases the level of long-term debt of split rated firms. The level of debt maturity for one-notch split rated firms are typically 2.1% (i.e., 3 × 0.007 = 0.021) higher when compared to the estimated debt maturity level for these firms if both CRAs had assigned the same superior ratings level. In the inferior rating model, the coefficient for *ASPLIT* (β_I) is 0.005 for *DM3* (0.008 for *DM5*) and significant, suggesting that even with a superior rating, split ratings still significantly increase the level of long-term debt of split rated firms. Because the coefficients for *ASPLIT* in both the superior model and the inferior model are positive and significant, the actual debt maturity level of split rated firms are above the estimated level of these firms if both CRAs had assigned the same superior or inferior ratings level (as illustrated in Figure 4.C.1). The level of debt maturity for one-notch split rated firms are typically 1.5% (i.e., 3 × 0.005 = 0.015) higher when compared to the estimated debt maturity level for these firms if both CRAs had assigned the same inferior ratings level. This suggests that the threat of getting downgraded by CRAs, which arises from split ratings, on firms' debt maturity decisions is more significant and prominent than the benefit of additional superior second ratings.

The information risk is about 1.8% (i.e., (0.021 + 0.015)/2 = 0.018), suggesting that firms with split ratings have on average, a 1.8% higher debt maturity level than the average of estimated debt maturity of these firms if CRAs had assigned both superior and inferior ratings. The result indicates that split rated firms' managers consider split ratings as an additional information risk (apart from credit risk) when deciding the optimal level of long-term debt. Thus, the result is consistent with the baseline model, indicating that the baseline model is robust.

Table 4.C.1. Debt maturity, superior rating model and inferior rating model

Variables	Expected sign	Superior Rating Model DM3 (I)	Superior Rating Model DM5 (II)	Inferior Rating Model DM3 (III)	Inferior Rating Model DM5 (IV)
$ASPLIT_{t-1}$	+	0.007**	0.009**	0.005*	0.008**
		(2.48)	(2.35)	(1.67)	(2.33)
$TANG_{t-1}$	+	0.054**	0.066*	0.054**	0.064*
		(2.03)	(1.72)	(2.04)	(1.66)
FS_{t-1}	+	-0.005	0.011	-0.005	0.011
		(-0.96)	(1.62)	(-0.92)	(1.62)
MTB_{t-1}	-	-0.006	0.010	-0.007	0.010
		(-0.53)	(0.81)	(-0.66)	(0.78)
$PROFIT_{t-1}$	-	0.110	-0.071	0.118	-0.060
		(1.25)	(-0.61)	(1.33)	(-0.52)
RD_{t-1}	-	0.034	0.082	0.031	0.060
		(0.19)	(0.39)	(0.17)	(0.28)
EI_{t-1}	+	0.020***	0.022***	0.019***	0.022***
		(3.22)	(2.86)	(3.13)	(2.83)
AGE_{t-1}	+	-0.005	0.003	-0.005	0.003
		(-0.88)	(0.34)	(-0.95)	(0.33)
$INDDM_{t-1}$	+	0.095***	0.084***	0.096***	0.087***
		(4.79)	(3.09)	(4.87)	(3.20)
Constant		0.174***	0.183***	-0.011	-0.236
		(3.54)	(2.84)	(-0.10)	(-1.06)
Year *Industry Interactions		Yes	Yes	Yes	Yes
Superior Rating Level Dummies		Yes	Yes	No	No
Inferior Rating Level Dummies		No	No	Yes	Yes
Observations		6,630	6,630	6,630	6,630
Number of firms		884	884	884	884

Note: Table 4.C.1. reports the results of Eq. (4.C.1) and (4.C.2) using OLS estimation. The dependent variables *DM3* (*DM5*) are the ratio of long-term debt maturing in more than 3 (5) years over total debt at time *t*. The main independent variable is the split rating (*ASPLIT*), which is the rounded value of the absolute average daily rating differences between Moody's and S&P at time *t-1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry debt maturity (*INDDM*). See Table 4.1 for definitions. In the Superior (Inferior) Rating Model, the superior (inferior) rating of split rated firms are used to construct the rating dummy variables. The regressions include Year*Industry fixed effects. Values in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 4.2. ***, **, and * refers to significance at the 1%, 5%, 10% levels, respectively.

Chapter 5: Split ratings and corporate capital structure

5.1 Introduction

The aim of this Chapter is to investigate the impact of rating dispersion from credit rating agencies (CRAs) on firms' capital structure. Credit ratings play an important role in firms' financial management. They not only have a pivotal impact on firms' financing outcome but also on firms' optimal capital structure decisions. Firms that are on the verge of rating changes or after being downgraded use less debt in the hope of getting favourable rating actions in the future (Kisgen, 2006; 2009). Credit ratings also impact firms' real outcomes (Sufi, 2009; Lemmon and Roberts, 2010). A firm with better ratings subsequently has better capital market access, in terms of both the cost of debt and the amount of debt issuance, than a firm with lower ratings (Tang, 2009). On the other hand, firms with lower ratings tend to adjust to their optimal capital structure more rapidly (Wojewodzki et al., 2018). Almeida et al. (2017) suggest that firms change their investment behaviour and their reliance on credit markets in the presence of a sovereign rating downgrade (driven by the sovereign rating ceiling channel). In addition, credit ratings affect the firms' cost of capital (Kisgen and Strahan, 2010; Baghai et al., 2014), firms' access to the capital market (Frank and Goyal, 2009) and on firms' investment. Firms with ratings are more likely to take part in merger and acquisition than their unrated peers (Harford and Uysal, 2014) and they are more likely to use cash in these investment (Karampatsas et al., 2014). Overall, credit ratings have a significant impact on firms' financial policies, and they indeed matter for firms' managers in their decision regarding firms' capital structure.[60]

Any information regarding issuers' creditworthiness could lead to an adjustment of firms' capital structure. Credit rating literature has found that the market perceives ratings from both S&P and Moody's differently and there are systematic differences between these two CRAs (see, for example, Moon and Stotsky, 1993; Pottier and Sommer, 1999; Morgan, 2002; Livingston et al., 2010). As split ratings are common, prior literature has shown the significant impact of split ratings on firms' cost of debt and rating migrations. Firms with split ratings have higher bond yields (Morgan, 2002; Mahlmann, 2009; Livingston et al., 2010, Livingston and Zhou, 2010) and higher probability of receiving future rating actions (Livingston et al., 2008). Livingston et al. (2012) and Livingston and Zhou (2010) suggest that rating

[60] In their CFOs survey, Graham and Harvey (2001) find that credit ratings are the second most important factor for CFOs when considering firms' capital structure.

disagreement are a sign of potential information opacity problem within the firms. Information opacity is considered as information asymmetry between firms and investors (Ravi and Hong, 2014), and prior literature has shown that information asymmetry is an important determinant of capital structure decisions (Agarwal and O'Hara, 2007; Bharath et al., 2009; Petacchi, 2015). Hence, one might expect split ratings to have a significant impact on firms' leverage choices.

There are three main theories that explain capital structure decisions, namely, trade-off theory, pecking order theory and market-timing theory. The trade-off theory suggests that firms will choose to rely less on debt if the benefit from tax-shield is overweighed by the raising of cost of debt (Kraus and Litzenberger, 1973). Thus, according to the trade-off theory, firms with split ratings are encouraged to issue more equity than debt to avoid the likely higher borrowing cost arising from CRAs' disagreement. On the other hand, the pecking order theory suggests that firms' choice of financing sources is based on each source's level of adverse selection problem (from a minor problem to a serious problem: retained earnings, debt financing, equity financing) (Myers, 1984). This implies that firms with split ratings should issue more debt to mitigate the adverse selection problem arising from firms' information opacity issues. As a result, split rated firms should have a higher debt level than their non-split rated peers. According to the market-timing theory, firms' choices of funds are based on which types of the financial market are favourable at the time of financing (Frank and Goyal, 2009). Thus, all the arguments have their merits and pose an interesting research question regarding the effect of split ratings on firms' capital structure.[61]

In order to answer this research question, a sample of all listed U.S. corporations with long-term credit ratings from Moody's and S&P during the period of 2003 to 2015 is employed. The measure of split ratings is defined in the same way as in Section 3.4.4 of Chapter 3. Split ratings are calculated as the absolute annual average of daily differences at ratings/outlook/watch status between Moody's and S&P over a fiscal year. The reason for including outlook and watch status is to take into account effective rating announcements and information on imminent rating actions (Ferreira and Gamma, 2007). Capital structure (debt ratios) are defined using approaches employed in prior literature (e.g. Keefe and Yaghoubi, 2016). By using different measures, the empirical analysis exploits variation in capital structure arising from various definitions of liabilities or long-term debt (see Section 5.4.2 for details on capital structure definitions). Ordinary least square (OLS), Tobit, and generalized linear model (GLM) are used to investigate the effect of split ratings on firms' capital structure.

[61] See Section 5.3 for more details on these theories on capital structure decision.

The empirical results show that split rated firms have higher leverage than non-split rated firms with similar credit risk. The effect of split ratings is economically large, whereby 1-notch split rated firms, on average, have 1.2% to 1.5% higher market debt ratios than non-split rated firms. The finding suggests that firms with split ratings are more concerned about the information asymmetry and adverse selection problem than any potential increase in the borrowing cost arising from a current split rating. Firms that expose to greater information asymmetry and considerable adverse selection problem consequently rely more on debt than equity when it comes to financing decisions (Bharath et al., 2009; Petacchi, 2015). In addition, the results also show that split rated firms' managers do not differentiate between superior Moody's ratings and superior S&P ratings with respect to the optimal capital structure decisions. This suggests that even though superior Moody's split rated firms have lower borrowing cost (Livingston et al., 2010), firms' managers only focus on the impact of split ratings (regardless of which CRA assign higher ratings) when deciding the target capital structure.

This Chapter contributes to the literature on capital structure and the literature on credit ratings in two aspects. First, it examines the impact of split ratings on the firm's optimal level of capital structure. Second, it investigates whether superior ratings from one CRA have a different impact on firms' decision regarding capital structure than superior ratings from other CRA. No prior study has examined these issues and this study fills in these gaps in the literature. Most of the previous studies regarding credit ratings and capital structure only examine the effects of one CRA (either Moody's or S&P) and do not take into account the other. The finding of this Chapter suggests that credit ratings from both CRAs matter for firms and firms' manager do not differentiate which CRA has assigned the higher or lower ratings when considering the firms' capital structure. It reinforces the ongoing relevance of credit ratings in the sphere of corporate debt.

This Chapter is organized as follows: Section 5.2. reviews the existing literature about debt structure and credit ratings, Section 5.3. develops the hypotheses of the study, Section 5.4 explains research methodology while Section 5.5 describes the sample. The empirical results and interpretations are presented in Section 5.6 and Section 5.7. Section 5.8 concludes.

5.2 Literature review

Credit ratings play a very important role in the capability of firms to financing from external capital sources. Graham and Harvey (2001) is the first study that documented the importance of credit ratings on firms' manager behaviour toward capital policy. Conducting a survey of 392 CFOs, Graham and Harvey's (2001) find that U.S. firms' managers consider credit ratings as the second most important factors in their target capital structure policy, just behind financial flexibility. Kisgen (2006) investigates how firms' behaviour changes under the impact of credit ratings using all U.S. firms rated by S&P during the period of 1986 to 2001. The author shows that firms are more likely to use less debt if they are at the edge of rating changes, e.g. firms with plus or minus status within a rating category (e.g. A+ or A− within rating A category). This finding suggests that firms with a positive status do not prefer to issue more debt to secure a rating upgrade to higher rating category. On the other hand, a firm with a negative status prefers not to issue new debt to avoid getting downgraded to a lower rating category.

In follow-up research, Kisgen (2009) examines the U.S. firms' financial behaviour after receiving rating changes by S&P during 1986 to 2003, showing that firms consequently change their capital structure policy by issuing less debt after receiving rating downgrades. However, the study does not find any significant effect of rating upgrades on future firms' capital structure. This behaviour is a reasonable response to the credit rating – credit structure theory of Kisgen (2006). Firms seek to get back to a higher credit rating category by reducing debt or not issuing new debts and thus firms are expected to reduce leverage after their ratings being downgraded. In addition, Huang and Shen (2015) find that firms rated by S&P significantly adjust their capital structure in the presence of rating downgrades rather than upgrades. They also find that the speed of adjustment is faster for firms in strong legal and institutional environments and in countries in better financial conditions. Consistent with Huang and Shen's (2015) findings, Wojewodzki et al. (2018) find that credit ratings have negative effects on firms' leverage in countries with more market-based financial systems (countries in which stock markets are larger and more liquid) and that firms with poorer ratings adjust more rapid toward target leverages than firms with higher ratings. However, both Huang and Shen (2015) and Wojewodzki et al. (2018) use firms in 58 countries and 19 countries, respectively (including the U.S.) rather than a sample of U.S. firms only employed by Kisgen (2006, 2009).[62]

Baghai et al. (2014) investigate the change in rating standards from three major CRAs, S&P, Moody's and Fitch, and its impact on firms' capital structure and debt pricing. They find that CRAs have become more conservative over time and firms affected by conservatism use less debt and have lower leverage. This finding further confirms the important role of credit ratings on firms' capital structure decisions. Consistent with Kisgen (2006, 2009), Goyal and

[62] Nevertheless, Kisgen (2006, 2009), Huang and Shen (2015) and Wojewodzki et al. (2018) employ credit ratings from S&P only.

Wang (2013) show a negative relation between debt issuances and ratings as they investigate debt rating actions following debt issuances. They suggest that firms' ratings are improved with the increases in firms' profitability and for larger firms while worsened with the increase in leverage. In addition, Cornaggia et al., (2018) find that even though the reputation of CRAs was affected following the subprime crisis, investors and issuers are still rely on credit ratings and that credit ratings significant affect the cost of securities.

Apart from these studies, the capital structure literature mostly use credit ratings as a control variable for supply-side factors/debt market access (see, for example, Faulkender and Petersen, 2006; Frank and Goyal, 2009; Bharath et al., 2009; Danis et al., 2014; Elsas and Florysiak, 2015), or as a control variable for the quality of credit ratings (investment-grade or speculative grade) (Frank and Goyal, 2009; Kemper and Rao, 2013; Keefe and Yaghoubi, 2016). Based on existing literature, being rated have a positive impact on the firms' leverage. It suggests that firms with credit ratings have better access to the debt market and thus issue more debt than non-rated firms. Faulkender and Peterson (2006) find that firms with access to public debt markets have 50% higher leverage ratios than those without. Furthermore, having a better credit rating affects firms' debt capacity and debt quality. Frank and Goyal (2009) argue that firms with high ratings' levels have lower information asymmetry and adverse selections than others. Rauh and Sufi (2010) find that low credit quality firms are more likely to rely on costly forms of debt financing than their high credit quality peers. Billett et al. (2011) find that firms with better credit quality have higher debt capacity than others as they experience lower cost of debt.

Most of the studies in the capital structure literature focus on either one of the two major CRAs, S&P (e.g. Bharath et al., 2009; Frank and Goyal, 2009; Kisgen, 2006, 2009; Keefe and Yaghoubi, 2016) or Moody's (Roberts and Sufi, 2009; Rauh and Sufi, 2010). However, to the best of my knowledge, only Ismail et al., (2015) examine the effect of both CRAs on firms' capital structure. Considering the relationship between split rating and debt-signalling in nine emerging and five advanced bond markets (including the U.S.), Ismail et al. (2015) show that firms can minimize the chances of being split rated by setting their debt-to-equity ratios at an optimal level. Firms in emerging markets can reduce their cost of debt for their respective bonds by obtaining an optimal capital structure and consequently diminishing the effect of information asymmetry proxy by split ratings. Nevertheless, they find no evidence of the same effect in advanced bond markets. They argue that in emerging markets, where firm performance information is relatively scarce, information asymmetry (split ratings) could have a more significant impact on firms cost of capital than in advance market. However, their results could suffer from the selection bias because their sample size (313 firms across 13 countries) is relatively small compared to other related studies.

Recent credit rating literature also focuses on the link between bond market access (having credit ratings) and investment decisions. Harford and Uysal (2014) find that firms with bond market access are more likely to undertake acquisitions than their unrated peers. They further argue that the lack of debt market access hinders firms from making investments as well as affect the quality of these investments. Furthermore, Karampatsas et al. (2014) find that firms with better access to the debt market (because they have high credit quality) are more likely to use cash financing in mergers and acquisitions. They argue that firms with better credit ratings have little finance constraints and can more easily issue public debts and because of that, those firms could take advantage of the cash payment in acquisitions.[63] This suggests that credit ratings affect both firms' investment decisions as well as firms' choice of payment methods.

To sum up, while credit ratings are one of the most important factors for firms' manager to consider when making decisions on firms' capital structure, the effect of the different opinion between CRAs on a firms' capital structure has not yet been investigated. Credit ratings have an important role in firms' financing and investing behaviour. Disagreements between CRAs on firms' creditworthiness provide market participants with new information about firms' information asymmetry/information opaqueness problem. Therefore, examining the impact of split ratings between CRAs on capital structures can provide a number of insights into firms' capital structure decisions.

5.3 Research hypotheses

To examine the impact of split ratings on corporate capital structure, two different hypotheses are proposed. Hypothesis 1 is as follows:

H_{1A}: Split ratings have a significant effect on the capital structure.

H_{1N} suggests that firms with split rating do not change their capital structure. If the null hypothesis is rejected, firms' managers recognize the effect of rating ambiguity of CRAs about firms' credit risk upon debt and equity market and act accordingly. Firms with split ratings have a higher cost of debt than non-split rated firms with similar default risk categories (see, for example, Livingston and Zhou, 2008; Livingston et al., 2010). On the other hand, split

[63] Firms using cash financing experience non-negative abnormal returns in mergers and acquisitions (e.g. Moeller et al., 2004; Schlingemann, 2004)

ratings also increase the cost of equity capital of split rated firms compared to non-split rated firms (see, for example, Chapter 3). Thus, rating disagreements between two CRAs affects not only the debt market but also the equity market and that, in turn, have a significant impact on the decision of managers upon capital structures. In the existing literature, there are three capital structure theories explaining the capital structure decisions: the trade-off theory, the pecking order theory, and the market timing theory.

The Kraus and Litzenberger's (1973) trade-off theory demonstrates that firms' optimal capital structure is the trade-off between the tax benefit of debt and the costs of bankruptcy. They suggest that firms trade-off the marginal cost of debt against the marginal benefit of tax shields. Thus, the raising of the cost of debt triggered by split ratings may be sufficiently high enough to encourage firms moving towards the zero-debt policy and issue less debt. As a result, split ratings will have a significant impact on the capital structure by lowering the proportion of debt. This suggests that a firm with split ratings uses less debt. However, one drawback of the trade-off theory in this situation is that it does not take into account the effect of rating disagreement on the equity market.

The second theory in the capital structure literature is the pecking order theory (Myers, 1984). The theory considers the three sources of funds that firms are able to access: retained earnings, debt, and equity. Frank and Goyal (2009) argue that due to the level of adverse selection, equity has a serious problem, debt has a minor problem, while retained earnings have no adverse selection problem. First, from the firm managers' point of view, retained earnings are always used as possible as it is a better source of funding than outside funding. Second, if retained earnings are not possible, managers then consider issuing debt. Finally, equity issuance is the choice of last resort. From the perspective of outsider investors, Frank and Goyal (2009) suggest that "equity is strictly riskier than debt". Thus, a firm announces issuing equity will trigger investors to re-evaluate that firm's equity and a fall in equity valuation makes the decision of financing by equity less attractive to firm managers. Additionally, prior research has shown that firms with high information asymmetry in equity market use more debt financing than firms with low level of information asymmetry (Bharath et al., 2009; Petacchi, 2015). Since split ratings are a signal of uncertainty and ambiguity surrounding firms' creditworthiness, they also are a proxy of firms' information asymmetry. Thus, split rated firms, which experience higher information asymmetry, are expected to use more debt than non-split rated firms. Overall, considering the effect of split ratings on both the debt and equity market, the pecking order theory suggests that firms will issue more debt relatively to equity as the financing choice.

Finally, the market timing theory suggests that firms' managers consider the condition of both the debt and equity market and choose the more favourable market (Frank and Goyal, 2009). If the market conditions look unusually favourable, firms may raise funds even if they currently have no project to finance. The idea is supported by the survey conducted by Graham and Harvey (2001). The theory suggests that the condition of both equity and bond markets are important to managers' decision of capital structure. Hence, the change of the levels of capital structure will be affected by the condition of the debt and equity market. Chapter 3 shows that the cost of equity for split rated firms are significantly higher than non-split rated firms and the magnitude of the increase are stronger than for the cost of debt. Thus, this makes debt market financing to be more favourable than equity market financing. Additionally, Petacchi (2015) suggests that firm managers rely more on debt when facing a higher cost of equity associated with firms' information asymmetry. Since split ratings are the result of firms' information opaqueness (information asymmetry between firms and investors), firms may choose to raise funds via debt financing than equity financing if there is uncertainty with regard to firms' creditworthiness. Thus, split ratings might have a significant impact on firm's levels of capital structure by increasing the proportion of debt. Overall, pecking order and market timing theory suggest that split rated firm have a higher optimal debt level compared to their non-split rated peers.

The second hypothesis is related to whether superior ratings from one of the two major CRAs, Moody's and S&P, have relevant information to issuers and investors.

H_{2A}: Superior or inferior ratings from Moody's versus S&P have a significant impact on firms' capital structure.

Livingston et al. (2010) investigate the impact of split ratings between Moody's and S&P on bond's yields and find that firms with superior Moody's ratings have significantly lower bond yields than firms with superior S&P ratings, suggesting the cost of debt of firms with superior Moody's rating differ from that of firms with superior S&P rating. Moreover, the results of Chapter 3 show that firms' shareholder and managers put more weight on S&P ratings than Moody's when assessing the cost of equity. Thus, superior ratings from S&P have a different impact on both the cost of debt and the cost of equity capital than firms with superior ratings from Moody's. Therefore, a firm with a superior Moody's rating is expected to issue more debt and less equity than a firm with superior S&P's rating because that firm has a lower cost of debt and higher cost of equity capital. On the other hand, a firm with superior S&P rating will have a higher cost of debt and lower cost of equity capital, and hence it might prefer raising funds through equity market than through debt market and thus lower its' debt ratios.

5.4 Research design

5.4.1 Split ratings impact on capital structure

In order to examine the relationship between split ratings and capital structure (H_{1A}), the following model is employed:

$$RATIO_{i,t} = \beta_0 + \beta_1 ASPLIT_{i,t-1} + \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t-1} + \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \quad (5.1)$$

For each firm *i* in year *t*, $RATIO_{i,t}$ is the debt ratio (*MDR1*, *BDR1*, *MDR2*, *BDR2*, *MDR3*, and *BDR3*; see Section 5.4.2 for more detail), $ASPLIT_{i,\,t-1}$ is the absolute split ratings of firm *i* in year $t-1$ calculated as the absolute annual average of daily differences between Moody's and S&P (based on 58-unit CCR scale) over a fiscal year (see Section 5.4.3 for more details). H_{1A} predicts that split ratings have a significant impact on to firms' capital structure and thus $\beta_1 > 0$ ($\beta_1 < 0$). $CONTROL_{i,j,t-1}$ is the *j* ($j = 8$) characteristics variables of firm *i* in year $t-1$. Similar to Section 4.4.4, the control variables in this Chapter include: market-to-book assets ratio (*MTB*), tangibility (*TANG*), profits (*PROFIT*), assets (*FS*), ratio of research & development expenses to sale (*R&D*), firm age (*AGE*), equity issues (*EI*) and median industry leverage (*INDFL*).[64] Previous literature (Frank and Goyal, 2009; Kisgen, 2009) finds that *AGE*, *TANG* and *FS* have a positive impact on firms' capital structure while *PROFIT*, *MTB*, *R&D* and *EI* have a negative effect on firms' capital structure. All variable definitions and constructions can be found in Table 5.1. $LEVEL_{i,k,t-1}$ is set of *k* ($k = 19$) rating level dummies, which is based on the rounded average of Moody's ratings and S&P ratings (based on the 20-notch rating scale). *YEAR*×*INDUSTRY* is the interaction term of year and industry dummy variables with *l* ($l = 13$) years and *m* ($m = 8$) industries based on 1-digit SIC code. There is an increasing number of literature which used interacting fixed effects (Jiménez et al., 2012; Klusak et al., 2017) as the benefit of this method is that the macroeconomic conditions can come directly from the interactions and extra-macroeconomic variables do not need to be included in the regression. The standard error is clustered at the firm level to account for heterogeneity across firms. Eq. (5.1) is also estimated using the heteroscedasticity-consistent standard errors (Huber-White standard errors) as a robustness test. The robust standard errors

[64] The median industry leverage (*INDFL*) is used in this chapter instead of the median industry debt maturity.

in this case correct for possible heteroskedasticity and is appropriate to be used as an estimate of the true variance of the least squares estimator (Greene, 2003).

Similar to Chapter 4, using the debt ratio (*$RATIO_{i,t}$*) as dependent variable also suffers the same problems with debt maturity ratio as both of these measures are ratio and bounced between 0 and 1. Thus, apart from the OLS approach, this chapter also employs Tobit and GLM model to deal with the ratio dependent variables (Barclay and Smith, 1995). See Chapter 4, Section 4.4.5 for more details about Tobit and GLM model.

To examine the effect of superior Moody's ratings or superior S&P ratings on the capital structure (H_{2A}), the following model is tested:

$$\begin{aligned} RATIO_{i,t} = {} & \beta_0 + \beta_1 SUP\_MOODY_{i,t-1} + \beta_2 SUP\_S\&P_{i,t-1} \\ & + \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} LEVEL_{i,k,t-1} \\ & + \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \end{aligned} \tag{5.2}$$

where $SUP\_MOODY_{i,t-1}$ ($SUP\_S\&P_{i,t-1}$) is a dummy variable, which equals to 1 if Moody's (S&P) rating is higher than S&P (Moody's) rating for firm *i* in year *t – 1*. *RATIO*, *CONTROL*, *LEVEL* and *YEAR×INDUSTRY* are defined as in Eq. (5.1). OLS, Tobit and GLM model are also used to estimate Eq. (5.2).

5.4.2 Capital structure

The goal of the H_{1A} is to examine the impact of split ratings on firms' capital structure decisions. Keefe and Yaghoubi (2016) and Welch (2011) criticize that the financial-debt-to-asset ratio is not a good measurement of capital structure. Welch (2011) argues that there are two problems of using the common financial-debt-to-asset ratio (FD/AT). First, non-liabilities should not be considered as equity. Second, capital structure changes should not be including equity-issuing activity. Welch (2011) finds that equity issuing and changes in capital structure are distinct and the correlation between these two are weak. Thus, Keefe and Yaghoubi (2016) and Welch (2011) argue that debt does not only consist of long-term debt but may also consist of both long-term debt and short-term debt or consist of non-financial liabilities or only long-term debt. Hence, they introduce a debt ratio that includes both short-term debt and long-term debt, only long-term debt, or debt ratio with all liabilities. Furthermore, with each definition of leverage, there are two distinct measures: book leverage and market leverage. In the existing literature about capital structure, scholars are inconsistent with their choices of which leverage to be used. Myers (1977) and Graham and Harvey (2001) argue that the book leverage ratio is more reliable, and firms' managers do not act upon the change of equity market movement. However, Welch (2004) suggests that market measure is more forward-looking, and book leverage ratio is primarily a "plug number", measuring what has taken place, and backwards-looking. Thus, following Keefe and Yaghoubi (2016), both book and market leverage ratio are used together with three different definitions of debt. Overall, six measures of capital structures are tested for the H_{1A}.

Among the three different definitions, all liabilities debt ratio is the broadest one. The all liabilities market debt ratio is defined as the ratio between total liabilities and total assets minus common equity plus market value of common equity.

$$MDR1 = \frac{lt}{(at - ceq) + csho * prcc\_f} \tag{5.3}$$

where *MDR1* is the all liabilities market debt ratio, *lt* is total liabilities, *at* is total assets, *ceq* is common equity, *csho* is common share outstanding and *prcc_f* is annual close price on the fiscal year-end basis.

The all liabilities book debt ratio is defined as the ratio between total liabilities and total assets.

$$BDR1 = \frac{lt}{at} \tag{5.4}$$

where *BDR1* is the total liability debt ratio.

The short-term and long-term market debt ratio is defined as the ratio of short and long-term debt and short and long-term debt plus market value of common equity:

$$MDR2 = \frac{dltt + dlc}{dltt + dlc + csho * prcc\_f} \tag{5.5}$$

where *MDR2* is the short-term and long-term market debt ratio, *dltt* is total long-term debt, *dlc* is total debt in current liabilities.

The short-term and long-term book debt ratio is defined as long and short-term debt divided by short and long-term debt plus common equity:

$$BDR2 = \frac{dltt + dlc}{dltt + dlc + ceq} \tag{5.6}$$

where *BDR2* is the short-term and long-term book debt ratio.

The only long-term market debt ratio is the total long-term debt divided by total long-term debt plus market value of common equity:

$$MDR3 = \frac{dltt}{dltt + csho * prcc\_f} \tag{5.7}$$

where *MDR3* is the long-term market debt ratio.

The short-term and long-term book debt ratio is defined as the ratio between long-term debt and long-term debt plus common equity:

$$BDR3 = \frac{dltt}{dltt + ceq} \tag{5.8}$$

where *BDR3* is the long-term book debt ratio.

5.4.3 Split ratings

Split ratings are defined similarly to Section 3.4.4. *ASPLIT is* estimated as the average of absolute daily differences between Moody's and S&P over a calendar year. Absolute split ratings then are rounded to the nearest integer to remove the effect of a short-lived split (temporary split) and for easier interpretation of the result in terms of CCR. In addition, more than 4-CCR units split ratings are grouped into one group because split ratings higher than 4 CCR units are uncommon (see Table 5.5).

The second approach of defining split ratings is to calculate split rating as the average of daily differences between Moody's and S&P. By doing so, the positive and negative of daily split are allowed to offset each other and the direction of split is preserved. Split ratings are also rounded to the nearest integer to remove the effect of the temporary split as aforementioned.

5.4.4 Tobit and GLM model

Given that capital structure ratios are proportional variables and they are bound between closed interval [0,1] and non-linear, using OLS regression (even though it is a common practice in corporate finance literature) is not the most efficient and could produce biased estimators. Thus, to rule out these issues, two different approaches, Tobit and GLM model, are employed.

Tobit model is a method that treats the proportion variable as a censored variable. Using this model, the data above one and below zero are treated as censored and unobservable. Thus, the variable is assumed to be normally distributed within the zero and one interval. The advantage of the Tobit model is that it takes into account the mixed discrete-continuous distribution aspect of the proportion variable. However, one drawback of Tobit model is that the proportion values outside the zero and one interval are undefinable and not because that they are censored/unobservable (Maddala, 1991; Kieschnick and McCullough, 2003). Thus, applying the Tobit model, a censored regression model, to a non-censored data would be inappropriate. Another drawback of the Tobit model is that it relies on the assumption of normal distribution of the dependent variable (within the interval of zero and one).

The OLS and Tobit model rely on the assumption that the disturbance term is homoscedastic and normal, GLM model, on the other hand, only specifies the first and second moments of the conditional distribution (Kieschnick and McCullough, 2003). This relaxes the needed condition on error term in the GLM model to only be independent and hence, the GLM model is more appropriate for the proportional dependent variable. In this chapter, the GLM model is used with the quasi-likelihood approach as suggested by Papke and Wooldridge (1996) (see Section 4.4.5 for more details).

5.4.5 Endogeneity issue

Similar to debt maturity (Section 4.4.5), the research design in this Chapter is also susceptible to endogeneity issues. In this Chapter, the main research design is less likely to suffer from the selection bias problem because the sampling process takes into account all population of U.S. corporation rated by both Moody's and S&P. However, simultaneity problem could be an issue as firms' choice of capital structure could, in turn, affect the probability of split rating occurrence. CRAs could anticipate the changes in firms' capital structure and reflect this information into credit ratings. If that is the case, both split ratings and capital structure are simultaneously defined each other. On the other hand, the main research design could potentially be affected by the omitted variable problem, where there are unobserved variables that affect both debt maturity and split ratings. In order to rule out both of these concerns, propensity score matching (PSM) is employed. Since PSM is a non-parametric method, it is less likely to suffer from the assumption's violation like endogeneity and thus, using PSM could justify the results from parametric models, such as OLS, Tobit and GLM (Li, 2013).

In order to construct a matched sample, a probit model is estimated to calculate the probability (propensity score) of a unit being treated (split rated):

$$\Phi^{-1}\big(e(\boldsymbol{X}_i)\big) = \boldsymbol{\beta}\mathbf{X}_i \tag{5.9}$$

where $\Phi()$ is the cumulative standard normal distributing function, $\boldsymbol{\beta}$ is the estimated coefficients vector of $\mathbf{X}_i$. $e(\boldsymbol{X}_i)$ is the propensity score of unit *i*. The characteristics $\mathbf{X}_i$ are firm size (*FS*), asset tangibility (*TANG*), book value of cash over total asset (*CASH*), market-to-book ratio (*MTB*), idiosyncratic risk (*IDIO*), taxes over total assets ratio (*TAXES*) as well as interaction terms of year and industry dummies and rating categories dummies (Gopalan et al., 2014; Almeida et al., 2017).

After the propensity scores are estimated, the treatment group (split rated group) and the control group (non-split rated group) are picked and a matched sample using matching methods is formed. The matching methods are used in this Chapter are the nearest neighbour matching (NN) with/without replacement, radius matching and kernel matching (see Section 3.4.6.4 and Table 3.3 for more details on these matching methods). Eq. (5.1) is re-estimated using the matched samples created from above in order to control for unbalanced covariates (that missing from probit model, Eq. (5.9)) and to produce a robust estimate of the average treatment effect on treated (ATT) (Schafer and Kang, 2008; Shadish et al., 2008).

5.5 Sample construction and data description

5.5.1 Sample construction

The data sample includes all listed U.S. corporation rated by the two major CRAs, Moody's and S&P, from 2003 to 2015. The reason for choosing 2003 as the started year is that the outlook status of Moody's issuers is only made available in their online database in that year. Annual data of U.S. corporations are obtained from the Compustat database. In addition, annual data are collected from 2002 since the lag of financial data is needed. Moody's and S&P ratings' data are collected from Moody's website and Capital IQ database, respectively. Following Keefe and Yaghoubi (2016) and Frank and Goyal (2009), firms that involve in a significant merger or acquisition (Compustat sales footnote code AB) are excluded from the sample.[65] One common practice in the capital structure literature (Fama and French, 2002; Frank and Goyal, 2003; Frank and Goyal, 2009; Keefe and Yaghoubi, 2016; Dang and Phan, 2016) is to exclude financial and utilities firms (SIC codes 6000-6999 and 4900-4999, accordingly); however, Kisgen (2006) argue that credit ratings also have a significant effect on these firms as well as industrial firms. Thus, these firms are included in the sample but robustness tests without their inclusion are also presented. Furthermore, any firms with

[65] Compustat net sales footnote AB reflects a significant merger/acquisition whereby the effects on the prior year's sales constitute 50% or more of the reported sales for that year. Thus, the reason of removing those firms is that firms involving in a major merger/acquisition experience so much changes in their sales, assets, liabilities, and debt structures that they are effectively outliers. Five removed firms are Activision Blizzard Inc (gvkey = 180405), Ceridian Corp (gvkey = 3480), Hexion Inc (gvkey = 2316), Resolute Forest Products Inc (gvkey = 2337), and United Continental Holdings Inc (gvkey = 10795).

negative common equity, total assets or net sales, or with missing net sales, total liabilities and total assets are excluded from the sample.[66] Following previous corporate finance literature (Keefe and Yaghoubi, 2016; Huang and Shang, 2019), missing research and development expenses (*xrd*) is set to be zero.[67]

Table 5.2 details the sampling process. Apart from removing missing data observations, all variables (except for *INDFL* and *ASPLIT*) are winsorized at 0.5% of both distribution tails to minimize the effect of outliers as well as the most extremely mis-recorded data.[68] Industry leverages (*INDFL*) are calculated as the median of all firms' leverage in the same industry, thus, they are the same for all companies in a specific industry. Hence, there is no need for winsorizing *INDFL*. Similarly, absolute rating splits (*ASPLIT*) are not winsorized because they do not contain any outliers.

5.5.2 Data description

Table 5.3 reports the summary statistics for all variables used. Means of all capital structure variables show that the more broadly debt ratios are defined, the higher they are. For example, the mean of all liabilities market debt ratio (*MDR1*) is the highest among the three market debt ratios, and the mean of long-term and short-term debt ratio (*MDR2*) are higher than the mean of only long-term market debt ratio (*MDR3*). The mean of *MDR1*, *MDR2*, and *MDR3* are 0.448, 0.306, and 0.287, respectively. Book debt ratios also show a similar pattern: the mean of *BDR1*, *BDR2*, and *BDR3* are 0.623, 0.460, and 0.435, respectively. Furthermore, the higher values of book debt ratios in comparison to market debt ratios are consistent with the above-1 mean of market to book ratio (*MTB*) (1.200). The mean of firm's size (*FS*) is 8.499 which is 4,909.86 million dollars total assets. Although Keefe and Yaghoubi's (2016) sample is from 1974 to 2012, the mean of firm size of the U.S. rated firms in this study are still much bigger than the mean of firm's size of all U.S. firms reported in Keefe and Yaghoubi (2016) which is only 4.642 million dollars. This suggests that firms rated by CRAs are generally large firms and have bigger book assets.

The mean of *SUP_MOODY* and *SUP_S&P* are 0.20 and 0.48, respectively. This suggests that the average firm in the sample faces a 20% likelihood of experiencing a split

[66] This is also a common practice in accounting and finance literature. Fama and French (1992), Griffin and Lemmon (2002) and Vassalou and Xing (2004) suggest excluding firms with negative common equity because they have high default risk.
[67] Additional robustness tests excluding missing *xrd* show similar results to baseline model.
[68] Similar to recording zero items as missing, Compustat often coded data items as zero if they were reported missing or combined with other data items (Frank and Goyal, 2009). Thus, winsorizing, the procedure of removing extreme values, help in dealing with this type of errors.

rating with superior Moody's ratings and 48% likelihood of getting a split rating with superior S&P ratings. This is consistent with Moody's being a more conservative CRAs than S&P in U.S. corporate ratings' market.

Figure 5.1 shows the mean of market debt ratios over the year. *MDR1* declines slowly from 2003, reaches a trough in 2006 and then skyrockets to its peak in 2008. This plot presents the effect of the 2007-2009 subprime mortgage crisis in the U.S. upon the debt market and especially the equity market. The crisis effect is more severe on the equity market reflected by the mean of book debt ratio figure. The changes of book debt ratios are less steep than market debt ratio, suggesting that the increase in firms' market debt ratio is mainly due to the drop in firms' equity value during the subprime crisis and only partially due to the shift from equity financing to debt financing. This indicates that the sub-prime mortgage crisis has a stronger impact on equity market than the capital market. For both market and book debt ratio, the all liabilities debt ratios (*MDR1*, *BDR1*) are systematically different from the other two (*MDR2*, *MDR3*, *BDR2*, *BDR3*) because all liabilities debt ratios are the broadest definitions among those debt ratios.

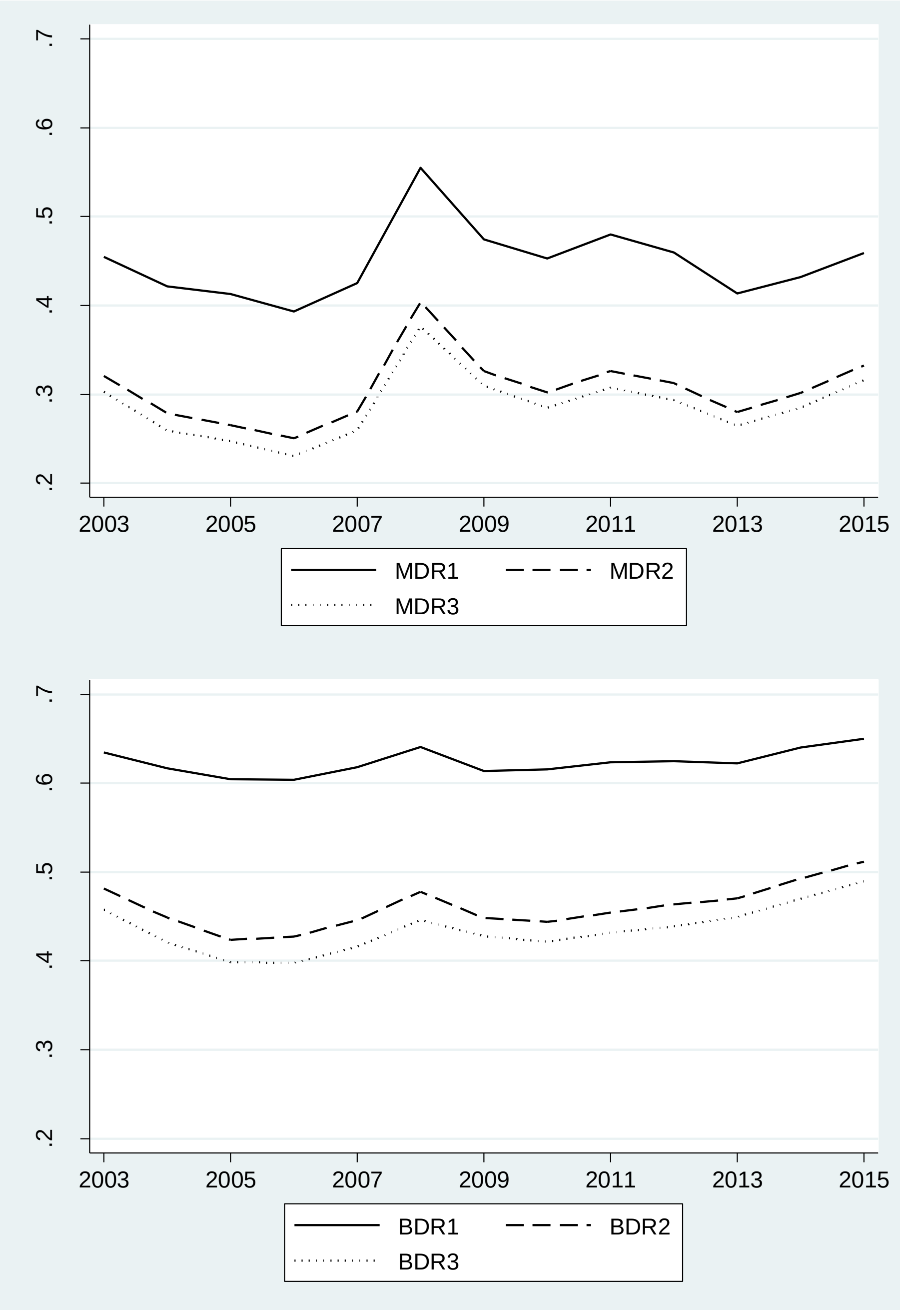

Figure 5.1. Mean of market and book debt ratios. Note: the mean of market and book debt ratios, *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2* and *BDR3*, over the sample period of 2003 – 2015.

Figure 5.2 plots market debt ratios and book debt ratios across the rating levels.[69] Figure 5.2 shows that both market and book debt ratios decline gradually from the lower rating level (Ca/CC/C/SD) to the higher rating level (Aaa/AAA), suggesting that firms with higher credit quality tend to use less debt and use more equity than firms with lower credit ratings. From a pecking order perspective, obtaining credit ratings is a process that involves revealing firms' private information to the public and consequently, reduce the information asymmetry and the adverse selection problem between firms and the lenders/investors. Odders-White and Ready

[69] The rating level variable is lagged consistent with Eq. (5.1).

(2005) present evidence of the link between the uncertainty about future firm value, adverse selection and credit ratings. They find that the adverse selection risk is larger when credit ratings are poorer, suggesting that credit ratings contain information about firms' adverse selection risk and the two measures of uncertainty are negatively correlated with each other. This also means that firms with higher credit ratings have less adverse selection problems. Therefore, firms with higher credit rating use more equity and less debt (Frank and Goyal, 2009). This indicates that not only the debt market but also equity market condition has a significant impact on rated firms, especially firms with high rating quality.

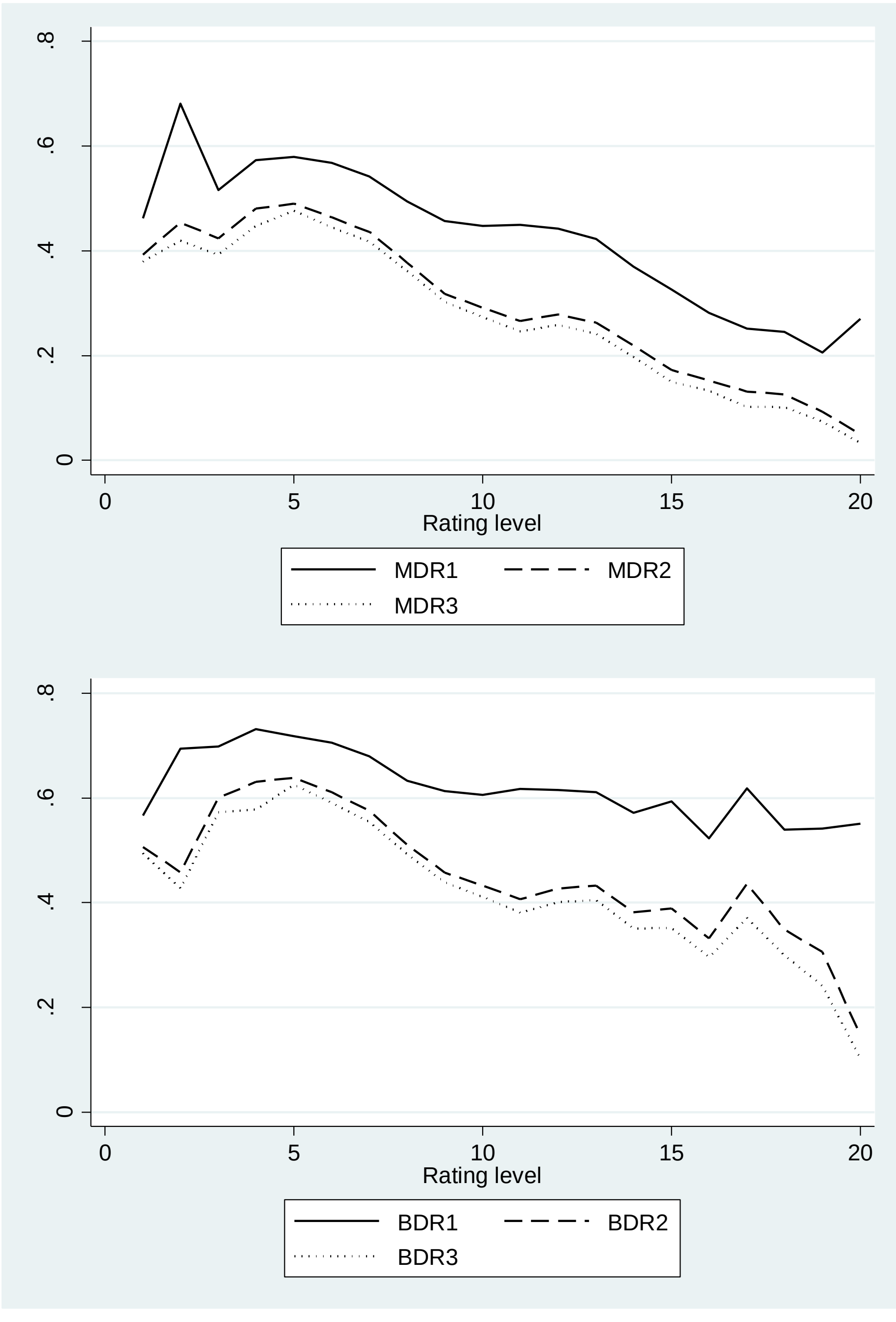

Figure 5.2. Mean of market and book debt ratios over different rating levels. Note: the mean of market and book debt ratios, *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2* and *BDR3*, over different rating levels (20-notch scale).

Table 5.4 shows the pairwise correlation matrix between explanatory variables. Split rating measure (*ASPLIT*) is negatively correlated with *FS*, *MTB*, *PROFIT*, *AGE*, and positively correlated with *RD* and *INDFL*. These correlation coefficients are at least statistically significant at the 5% level. This suggests that high split-rating firms are, on average, smaller, with fewer growth opportunities, less profitable, younger, have more R&D expenditures and operating in an industry with higher leverage.

Table 5.5 reports the detailed descriptions of split rating variables. Consistent with existing literature, split ratings account for approximately 70% of the total sample, suggesting that split ratings are common (Livingston et al., 2010). Additionally, large splits are uncommon as most of the split ratings are within 1 to 3 CCR interval, which account for more than three quarters of the number of split observations. Split with more than 13 CCR units only accounts for 0.2% (10 observations) of the total sample.[70] Furthermore, the proportion of split ratings of the total sample with superior S&P rating is 48.4% while that of superior Moody's rating is only 19.8%. This suggests that S&P is a more generous CRAs as it tends to assign more favourable ratings than Moody's. This finding is also consistent with Chapter 3, Chapter 4 and other literature (e.g. Livingston et al., 2012).

Figure 5.3 presents the number of split ratings and non-split across different rating levels as well as across years. As can be seen from the figure, across different rating levels, CRAs are more often disagree than agree with each other about firms' creditworthiness with only one exception of the highest possible rating level (rating level Aaa/AAA). Most of rating disagreements are falling in between rating level B2/B to rating level Baa1/BBB+ which are the rating level just under and right above the speculative/investment grade threshold. Another notable feature of split ratings is that CRAs disagree with each other more during the boom period (2003-2006) and then they become more consistent during and after the sub-prime mortgage crisis period (2007-2009). This shows the countercyclical property of CRAs. CRAs' ratings tend to be more inflated during the boom economic conditions and become more accurate during the stressed conditions (Bar-Isaac and Shapiro, 2013). Baghai et al. (2014) find that CRAs have become more conservative over time, and this also helps to explain the declining trend on split ratings from before the crisis and after the crisis.

[70] Split rated firms with more than 13 CCR units are Allied Waste Industries Inc (gvkey = 22140), Mediacom Communications Corp (gvkey = 129442), Merck & Co (gvkey = 7257), Sealed Air Corp (gvkey = 9555), Solutia Inc (gvkey = 65350), and Terra Industries Inc (gvkey = 5980).

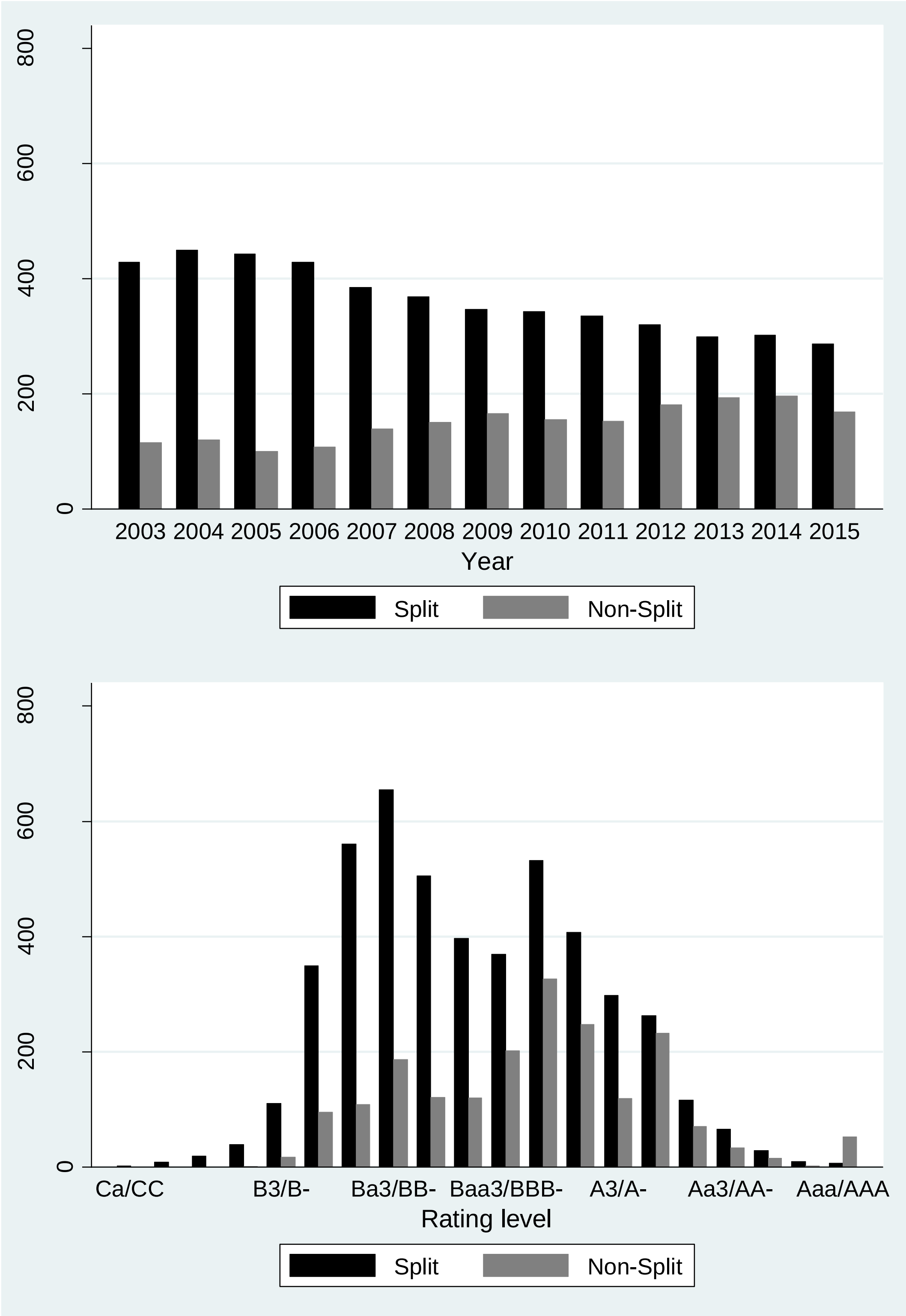

Figure 5.3. Number of split and non-split over years and different rating levels. Note: the number of split and non-split observations over years and different rating levels (20-notch scale).

Figure 5.4 shows the number of splits with superior Moody's rating and with superior S&P ratings. As can be seen from the graph, S&P assigns more often higher ratings than Moody's in almost every rating category, suggesting that S&P is a more generous CRA and Moody's is a more conservative CRA.

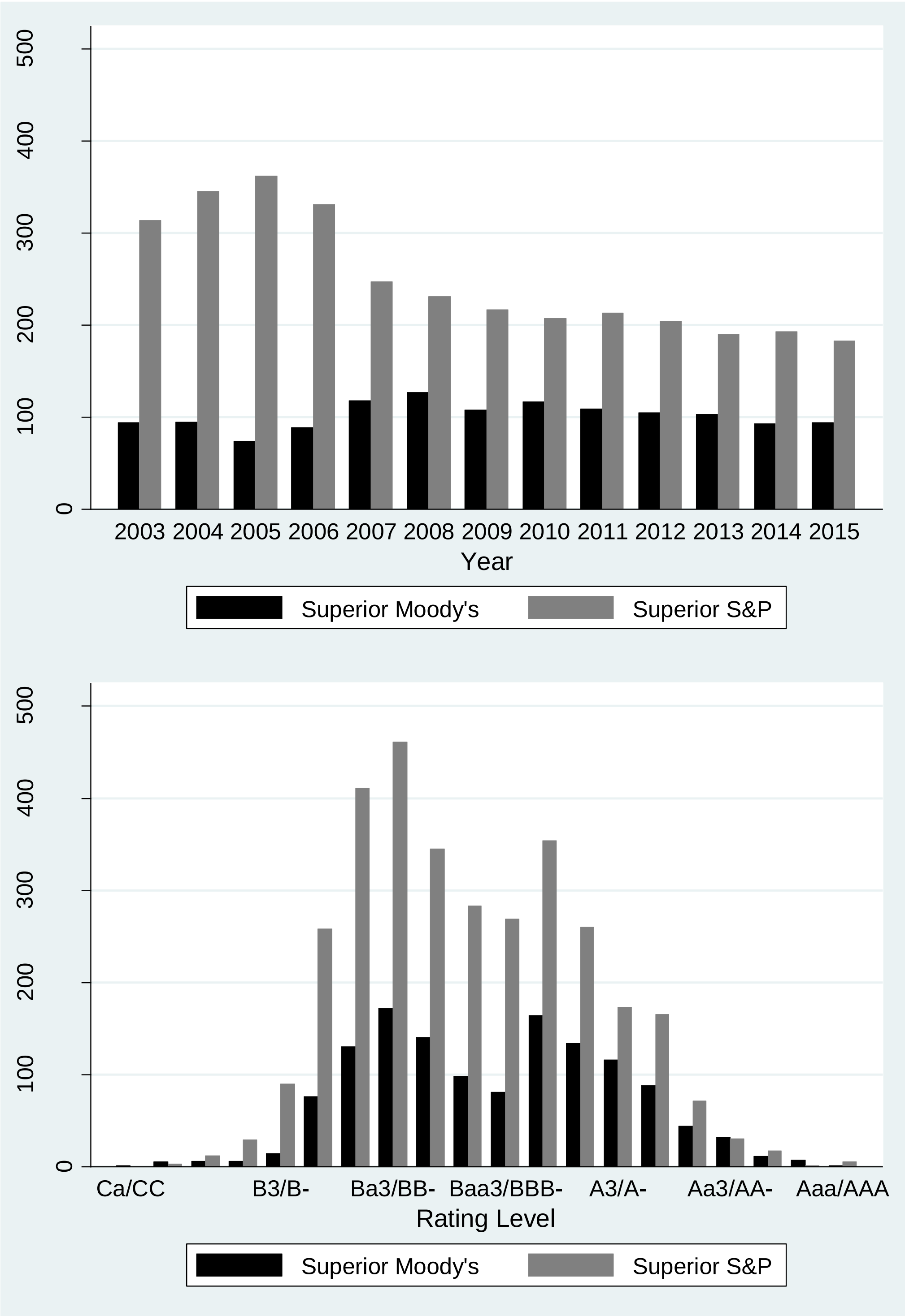

Figure 5.4. Number of splits with superior Moody's rating and splits with superior S&P rating over years and different rating levels. Note: the number of split ratings with superior Moody's rating and superior S&P rating over years and different rating levels (20-notch scale).

5.6 Empirical results

5.6.1 Split ratings and capital structure

Table 5.6 reports the results of the OLS model (Eq. (5.1)) that examines the impact of split ratings on firms' capital structure. The key variable of interest is $ASPLIT_{t-1}$ that captures the differences in ratings between Moody's and S&P in year $t-1$. The results reported in Table 5.6 are consistent with the sign predictions of H_{1A}. The coefficients of $ASPLIT_{t-1}$ on all 6 models are positive and significant at the 5% level at least, suggesting that firms with larger and/or more persistent split ratings on average have higher optimal leverage target than non-split rated firms.[71] For instance, when Moody's and S&P disagree on a firm's credit rating by one notch in year $t-1$, the firm has higher all liabilities market debt ratio (*MDR1*) and a higher total debt market debt ratio (*MDR2*) by about 1.5% in year *t* and a higher long-term debt market debt ratio (MDR3) by about 1.2%.[72] This change in the debt ratio shows that firms prefer to use more debt and less equity when the two major CRAs are uncertain about the firms' creditworthiness. The positive impact of split ratings on debt ratios are consistent across 6 market and book debt ratios. The results are consistent with the alternative hypothesis (H_{1A}) that split ratings have a significant effect on firms' levels of capital structure.

Credit ratings reveal private information to the public. As a result, firms with ratings have less adverse selection problem than firms without ratings. Split ratings signal the considerable ambiguity of firms' creditworthiness and therefore, also indicate the information asymmetry between firms and CRAs. In addition, previous literature finds that information opacity is one of the reasons that split ratings occur and split ratings are the sign of firms' information opaqueness problem (Morgan, 2002; Livingston and Zhou, 2008). Since information opacity implies information asymmetry problem between firms and investors (Ravi and Hong, 2014), firms with split ratings suffer from greater information asymmetry and consequently, greater adverse selection problem than non-split rated firms. Livingston et al. (2010) argue that bond investors recognize these information asymmetry problems of split rated firms and charge a premium for that (bonds of split rated firms has higher yield spreads than of non-split rated firms). The trade-off theory suggests that split rated firms have a higher cost of debt which might be sufficiently high to encourage firms to move toward less-debt

[71] Split rating variable (*ASPLIT*) are rounded to the nearest integer, thus, the regression only considers 'persistent' split ratings, which continue firmly for more than 6 months.
[72] Coefficients on $ASPLIT_{t-1}$ in Table 5.6 is for 1 CCR unit. The effect of a notch (3 CCR units) is then calculated by multiply the coefficient by 3.

policy. However, the pecking order theory suggests that a firm with split ratings should use more equity financing than debt financing because such firms have higher adverse selection problem. The results support the pecking order hypothesis. The results also support the market-timing hypothesis. Split rated firms issue more debt because the debt market is more favourable than the equity market (the cost of equity capital arising from split ratings is higher than the cost of debt – see Section 3.6.1). Pitacchi (2015) states that when considering capital structure, firms managers rely more on debt when they faced with a higher cost of equity. Thus, the results are also consistent with Petacchi's (2015) finding that high level of information asymmetry leads firms' managers to rely more on debt than equity when adjusting the target debt ratios or leverage. The result suggests that firms are more concerned about the information asymmetry and adverse selection problem arising from split ratings than the increased cost of debt and the risk of bankruptcy along with it.

The signs of the control variables' coefficients confirm the expectations when significant. Firm size has a positive coefficient as large, more diversified firms have lower default risk. Profitability has a negative coefficient because according to the pecking order theory, firms prefer to retain earnings than external funds and thus, more profitable firms will use less debt over time. Asset tangibility has a positive coefficient as tangible assets, such as property, plant, and equipment, are easier to value and can be the collateral for debt issuance and this will lower the expected cost of distress and debt-related agency problems.

Market-to-book ratio is a proxy of firm growth rate and firms with high market-to-book ratio consequently have higher costs of financial distress and debt-related agency problems. Growing firms rely more on equity investment and reduce leverage. Therefore, the market-to-book ratio is expected to have a negative impact on firm leverage. However, in Table 5.6 market-to-book ratio coefficients are positive in market debt ratio's models and negative in book debt ratio's models. These results are similar to Frank and Goyal (2009). They suggest that market debt ratio is forward-looking while book debt ratio is backward looking (see also Barclay et al., 2003) and the market-to-book ratio is a proxy of growth and therefore, possessing the ability to capture aspects of the firms' anticipate future. Thus, the impact of market-to-book ratio upon market debt ratio and book debt ratio are distinct from each other.

The ratio of R&D expenses to sales has a negative coefficient as firms with large discretionary expenses like R&D have fewer tangibility assets and consequently less debt. Equity issue has negative coefficient because firms issuing more equity consequently have less debt. Mature firms tend to have a better reputation and less debt-related agency costs and thus, firm age has a positive impact on leverage. Median industry leverage positively affects firm leverage. Firms' managers often use median industry leverage as a proxy for target debt ratio (Gilson, 1997; Hovakimian et al., 2001; Flannery and Rangan, 2006) and therefore, firms operating in high leverage industry tend to have higher leverage as well.

As mentioned in Section 5.4.4, using OLS regression for the proportional variables faces the challenge of the open interval (0, 1). Since proportional variables are bounded between zero and one interval, using OLS regression could result in the failure of taking into account "the qualitative difference between limit (zero) observations and non-limit (continuous) observation" (Greene, 2003). Tobit model and GLM model are employed as robustness tests. Table 5.B.1 and 5.B.2 in Appendix 5.B report the results of Eq. (5.1) with Tobit approach and GLM approach, respectively. As can be seen from both Table 5.B.1 and 5.B.2 in Appendix 5.B, the coefficients on split ratings (*ASPLIT*) are all positive and significant at least at the 5% level. In addition, the marginal effects of *ASPLIT* reported in both Tobit regression and GLM regression are consistent with the magnitude of split ratings in the baseline results.

To conclude, the results of Eq. (5.1) provide evidence of the significant impact of split ratings on firms' financial decision regarding capital structure. One notch split rated firms have higher market debt ratios by about 1.2% to 1.5% and higher book debt ratios by about 1.5% to 1.8% than non-split rated firms. These differences among firms' capital structure policy are the result of the information asymmetry problem of split rated firms. All the control variables' coefficients have the correct sign if significant. The results are robust using book ratio, market ratio, or different definitions of debt. The result suggests that split rated firms put more weight on the information asymmetry and adverse selection problem than the increased borrowing cost when assessing the optimal leverage target.

5.6.2 Cross-sectional tests

Similar to Chapter 4, to better understand the relation between split ratings and capital structure, a number of cross-sectional tests are implemented. All additional cross-sectional tests are estimated using OLS, Tobit and GLM model. Following Gopalan et al. (2014), six dummies are created and interacted with $ASPLIT_{t-1}$ in Eq. (5.1). The dummy variables are *SMALL*, (*1-SMALL*), *INVST*, (*1-INVST*), *CRISIS* and (*1-CRISIS*). *SMALL* is a dummy variable equal to 1 if a firm has a below-sample-median value of *FS* in year $t-1$ and 0 otherwise. *INVST* is a dummy variable equal to 1 if a firm has an investment-grade rating (Baa3/BBB- or above) in year $t-1$ and 0 otherwise. *CRISIS* is a dummy variable equal to 1 during the U.S. sub-prime crisis period (2007 – 2009) and 0 otherwise.

Table 5.7 reports the results of Eq. (5.1) with two interaction terms $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$. The test investigates whether small and large firms react differently after receiving split ratings. The coefficient on $ASPLIT_{t-1} \times SMALL_{t-1}$ are insignificant while those on $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$ are positive and significant at 1%, indicating that higher leverage ratios are only associated with large firms. The comparison of the two interaction terms' coefficients shows that the two coefficients are significantly different from each other for market debt ratio (see row titled ΔCOEF). All other control variables' signs are correct when significant.

The positive impact of split ratings on large firms' levels of capital structure could be due to that large firms are easier to access equity market and hence have higher equity to total assets ratio. Large firms with higher exposure of equity are more likely to be affected by the information asymmetry implied by split ratings and thus large firms with split ratings have higher leverage on average than non-split rated firms or small split rated firms. Small firms are more likely to rely on debt finance (for example, bank debt) rather than equity capital, thus, they are less likely to be affected by the information asymmetry associated with split ratings. This overall shows that the split ratings' impact on leverage is only associated with large firms but not small firms.

In addition to the OLS model, Eq. (5.1) with two interaction terms $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$ is re-estimated using Tobit and GLM model as robustness tests. The results are reported in Appendix 5.B - Table 5.B.3 and 5.B.4. The results from both of these models are consistent with the baseline results.

In Table 5.8, Eq. (5.1) is estimated using OLS model with two interaction terms (instead of *ASPLIT*) $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$, where *INVST* is a dummy that identifies firms with investment-grade ratings (average rating between S&P and Moody's is 11 or above based on 20-notch rating scale).[73] The test examines whether the effect of split ratings is different between investment grade and speculative grade -rated firms. The higher debt ratio is only associated with prior split ratings for firms with investment-grade ratings as the coefficients on $ASPLIT_{t-1} \times INVST_{t-1}$ are positive and significant at 1% level.

Figure 5.2 shows that firms with higher ratings have lower leverage ratios. Thus, investment grade rated firms have greater exposure to equity than speculative-grade rated firms. Since split ratings are a signal of information asymmetry/information opacity problem, firms

[73] Tobit and GLM model are also used and produce similar results compared to OLS model. Table 5.B.5 and Table 5.B.6 in Appendix 5.B provide the results for Tobit model and GLM model, respectively.

with greater exposure to equity are more likely to be rated at investment-grade and are more likely to have a higher level of leverage. This finding is consistent with the previous test between small and large firms (see Table 5.7), where the capital structure of firms with higher exposure to equity are more likely to be affected by split ratings. Overall, higher and persistence split ratings are associated with the higher debt level only for firms with investment-grade ratings or large size firms.

Table 5.9 reports the results of Eq. (5.1) using OLS model with two interaction terms, $ASPLIT_{t-1} \times CRISIS_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$, where *CRISIS* is a dummy that identifies the crisis period (2007 – 2009).[74] The results show that coefficients of $ASPLIT_{t-1} \times CRISIS_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$ are positive and significant for all market debt ratios while only $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$ are significant for book debt ratios. This implies that split ratings have a positive impact on market debt ratios during both crisis and non-crisis periods while they are only positively associated with higher levels of book capital structure during non-crisis periods. A possible reason for this finding is that market debt ratios are forward-looking while book debt ratios are backwards-looking, and the subprime crisis has a huge impact on the equity market, a forward-looking market. The coefficients of control variables have correct signs if significant.

5.6.3 Endogeneity

Similar to Chapter 4, a major concern about the relationship between split ratings and capital structure is the potential endogeneity. Endogeneity could come from three different problems: selection bias problem, simultaneity/reverse causality problem or omitted variables problem. Thus, in order to rule out these concerns, PSM is employed to construct a matching sample with treatment (split rated) firms and matched control (non-split rated) firms. The treatment in this chapter is whether firms have split ratings from CRAs or not (see Section 3.4.6 in Chapter 3 for more details).

The main matching method used in this chapter is NN matching without replacement and with the caliper band of 0.01. The propensity score is estimated using Eq. (5.9). A matched sample of 2,480 firm-year equally distributed between treated and control groups is obtained. Table 5.10 reports that matching quality evaluations for the NN matching without replacement and with a caliper of 0.01. Panel A of Table 5.10 shows the descriptive statistics of unmatched and matched covariates. All of the unmatched covariates have a high standardised bias,

[74] Table 5.B.7 and Table 5.B.8 in Appendix 5.B reports the results using Tobit and GLM model, respectively, and they are consistent with the OLS model results.

especially for IDIO, TAXES and FS (32.5%, -32.7% and -35.6% standardised bias, respectively). However, the standardised bias for all matched covariates is below 5%, which is the sufficient level of bias reduction suggested by prior literature (Caliendo and Kopeinig, 2008; Pan and Bai, 2015). In addition, all the unmatched sample's t-tests for significant differences between covariate means of treated group and control group are significant at the 1% and 5% level while those of matched sample are rejected at 10%, suggesting there are no significant differences between covariates' distribution after matching (covariates are balanced in both treated and control group).

Panel B of Table 5.10 shows the results of ATT for all dependent variables (*MDR1*, *BDR1*, *MDR2*, *BDR2*, *MDR3* and *BDR3*). All matched sample's ATT are positive and significant at the 5% level, suggesting that there is a significant difference in the mean of capital structure between split rated firms and non-split rated firms in the matched samples. In addition, Panel C of Table 5.10 reports the joint significant test and Pseudo R^2 between the unmatched sample and matched sample. The Pseudo R^2 for the matched sample is only 1.1%, which is much lower than 10.8% of the unmatched sample, while the joint significant F-test of the matched sample cannot be rejected, indicating the matched sample's covariates are indeed balanced in both treated and untreated group. Overall, all the tests suggest the propensity score specifications and matching methods are sufficient as well as the matched sample is well-balanced.

Table 5.11 reports the results of the probit regression (Eq. (5.9), Column (I)) and of the main regression (Eq. (5.1)) with the matched sample using OLS (Column (II) to (VII)). The coefficient of *IDIO* is positive and significant at the 1% level, suggesting that firms with high return volatility are more likely to be split rated. The coefficient of *TAXES* is negative and significant at the 1% level, suggesting that firms with larger taxes expenses are less likely to be split rated. Furthermore, the regression results estimated using Eq. (5.1) with the matched sample are similar to those of the baseline model, with the coefficients of $ASPLIT_{t-1}$ are positive and significant at the 1% level across column (II) to (VII).[75]

In addition, various matching approaches – including NN matching with replacement, radius matching and kernel matching are used as robustness tests. Table 5.B.11, 5.B.12, 5.B.13 and 5.B.14 in Appendix 5.B report the results of the matching quality tests and OLS, Tobit and GLM regression results of the NN matching with replacement and caliper of 0.01. Table 5.B.15,

[75] In addition to OLS regression, Eq. (5.1) is estimated with the matched sample using Tobit and GLM approach. The Tobit and GLM results are reported in Table 5.B.9 and Table 5.B.10, respectively. The results from both of these approaches are consistent with the OLS as well as the baseline regression.

5.B.16, 5.B.17 and 5.B.18 in Appendix 5.B report the results of the matching quality tests and OLS, Tobit and GLM regression results of the radius matching and with a caliper of 0.01. Table 5.B.19, 5.B.20, 5.B.21 and 5.B.22 in Appendix 5.B report the results of the matching quality tests and OLS, Tobit and GLM regression results of the kernel matching using Epanechnikov kernel function and bandwidth of 0.06. Overall, the results from all these matching approaches are consistent with results of the baseline model, suggesting the research design is robust with regards to endogeneity issue.

5.6.4 Additional robustness tests

5.6.4.1 Different definitions of split ratings

In this section, various definitions of split ratings are used as robustness tests. The first robustness test is to use a dummy variable (*SPLIT_DUM*) for split ratings. The results are reported in Table 5.B.23, 5.B.24 and 5.B.25 in Appendix 5.B. The coefficients for split dummy variable are positive and significant at the 1% level. These results are consistent with earlier results in Table 5.6. The coefficients of *SPLIT_DUM* for book market ratios are ranged from 0.024 to 0.028 while those for market debt ratios are about 0.020 to 0.022, suggesting that split rated firms have higher market debt ratios by about 2.0% to 2.2% and higher book debt ratios by about 2.4% to 2.8% than non-split rated firms.

To address the concern of the smoothening by rounding up the split ratings, another split rating variable ($ASPLIT\_R_{t-1}$) is introduced. $ASPLIT\_R_{t-1}$ is calculated as the absolute average of daily differences between Moody’s and S&P over a fiscal year and only rounded when $ASPLIT\_R_{t-1} < 0.5$ (to remove the effect of temporary split/split over less than 6 months). Table 5.B.26, 5.B.27 and 5.B.28 report the results of Eq. (5.1) with OLS, Tobit and GLM model with $ASPLIT\_R_{t-1}$ as the key independent variable. The results from these models are consistent with the baseline model with split ratings’ coefficients are positive and significant.

5.6.4.2 Excluding missing R&D expenses (xrd).

In Section 5.4.1, when calculating *RD* variable, missing *xrd* is set to be zero. This is a common practice when it comes to missing R&D expenses in the Compustat database (see, for example, Keefe and Yaghoubi, 2016; Huang and Shang, 2019). Thus, a robustness test with a sample excluding missing *xrd* is employed. Table 5.B.29, 5.B.30 and 5.B.31 in Appendix 5.B report the results of Eq. (5.1) with samples excluding missing *xrd*. As can be seen, the results are consistent with the baseline results.

5.6.4.3 Financial and utility firms.

Some prior studies in the capital structure literature (e.g. Frank and Goyal, 2009; Keefe and Yaghoubi, 2016) exclude financial (SIC codes 6000-6999) and utility companies (SIC codes 4900-4999) from the main sample as the financial structure of these firms are significantly different from firms from other industries. In the main results, financial and utility firms are included in the sample as ratings are likely to have an effect on those firms as well as industrial firms (Kisgen, 2006). However, in this section, Eq. (5.1) is estimated using a sub-sample excluding financial and utility firms and Table 5.B.32, 5.B.33 and 5.B.34 report the results. The coefficients of *ASPLIT* are positive and significant. These results are consistent with the main results, implying that the main results are not driven by the effect of the exclusion of financial and utility firms.

5.6.4.4 Livingston and Zhou's (2010) methodology

Similar to Chapters 3 and 4, the main research design of Chapter 5 uses rounded average ratings from Moody's and S&P as rating levels and this poses a potential problem when there are cases of Moody's and S&P ratings differing by one notch (i.e., BBB+ and BBB). Thus, this Chapter also employs the approach used by Livingston and Zhou's (2010) as a robustness test for this issue. Appendix 5.C provides details on the design and empirical results from this method.

Tables 5.C.1 and 5.C.2 in Appendix 5.C report the results of testing the superior and inferior models using Eq. (5.C.1) and Eq. (5.C.2). The coefficients on the split rating variables (*ASPLIT*) on all superior models are positive and significant while those on the inferior model are negative and marginally significant (except for *MDR1* and *BDR1*). This suggests that the actual level of debt maturity of split rated firms lies within the two estimated debt maturity levels of these firms if both CRAs had assigned the same ratings, inferior and superior ratings. In addition, on average, one-notch split rated firms have 0.9% higher level of leverage (*MDR1*) than the average of estimated leverage of these firms if both CRAs had assigned the same superior ratings and inferior ratings. This suggests that the information asymmetry risk arising from split ratings do indeed have a significant impact on firms' capital structure apart from the credit risk. Thus, this result is consistent with the baseline results and the main models are robust. The additional test is beneficial in reinforcing the inferences of this chapter.

5.7 Superior S&P ratings versus superior Moody's ratings and capital structure

Cost of debt literature (e.g. Livingston et al., 2010) has found that firms with higher Moody's ratings have lower bond yield spread than firms with higher S&P ratings and that investors do differentiate between superior Moody's ratings and superior S&P ratings. Thus, the question is whether firms' decisions regarding their capital structure differ when having superior Moody's ratings or superior S&P ratings.

Table 5.12 shows the regression results of Eq. (5.2) with two dummy variables, *SUP_MOODY* and *SUP_S&P*. *SUP_MOODY* (*SUP_S&P*) is a dummy variable which is equal to 1 if Moody's (S&P) rating is higher than S&P (Moody's), and 0 otherwise.[76] The coefficients on SUP_MOODY_{t-1} and $SUP\_S\&P_{t-1}$ are both positive and highly significant for all debt ratios. The positive coefficients of SUP_MOODY_{t-1} and $SUP\_S\&P_{t-1}$ further confirm that firms prefer debt financing than equity financing when they are split rated and that the effect of split ratings on capital structure is not driven solely by whether Moody's or S&P ratings are superior.

Livingston et al. (2010) and Livingston and Zhou (2010) find that firms with superior Moody's rating have a lower cost of debt than firms with superior S&P ratings. They argue that debt investors consider Moody's to be a more accurate CRA and place more weight on Moody's ratings while assessing firms' cost of debt. Thus, firms with superior S&P have significant higher borrowing cost than firms with superior Moody's. If this hold and everything else is equal, then split rated firms with superior Moody's ratings should issue more debt than split rated firms with superior S&P ratings because of the lower borrowing cost. The coefficients on SUP_MOODY_{t-1} is higher than the coefficients on $SUP\_S\&P_{t-1}$ in almost every case of debt ratios (except for *BDR3*). However, the equality test between the two variables' coefficients shows that the two coefficients are not significantly different from each other (see row titled ΔCOEF). This suggests that the effects of superior Moody's ratings and superior S&P ratings on firms' levels of capital structure are not significantly different from each other. This finding indicates that split rated firms do not differentiate between whose assigns higher rating when they decide their optimal level of leverage. These results are contrasted with those of Chapter 3 and Chapter 4, where equity investors and firms' manager

[76] Table 5.B.35 and Table 5.B.36 show the results of Eq. (4.2) with Tobit and GLM approach, respectively. The results from those are still robust.

differentiate between superior Moody's ratings and superior S&P ratings when assessing cost of equity capital and debt maturity structure, respectively.

Overall, when it comes to split ratings, firms' behaviour regarding the capital structure is different from outside investors. While debt investors put more emphasis on the more conservative CRA, Moody's, than the more generous CRA, S&P, firms do not differentiate between these two CRAs when assessing optimal capital structure. The reason of this behaviour could be that firms perceive split ratings as a signal of information opaqueness/information asymmetry problem to outside investors and that superior ratings from one particular CRA do not provide any positive additional information about these problems.

5.8 Conclusion

This Chapter investigates the impact of CRAs' disagreement on firms' creditworthiness on firms' capital structure decisions. A sample includes all listed U.S. corporations that are rated by both Moody's and S&P over the period from 2003 to 2015 is employed. Firms have average market debt ratios of less than 50% (MDR1, MDR2 and MDR3 are 46%, 31% and 29%, respectively), suggesting that rated firms rely more heavily on equity financing than debt financing. About 70% of firms in the sample are split rated over the sample period, suggesting that CRAs' disagreement upon firms' creditworthiness are common. The descriptive statistics of split ratings also show that Moody's is a more conservative than S&P, whereby 48% of firms with split ratings have superior S&P ratings and only 20% of firms with split ratings have superior Moody's ratings.

This Chapter hypothesizes that split ratings could have a significant impact on firms' optimal capital structure. On one hand, the trade-off theory suggests that firms' decisions regarding the capital structure are based on the trade-off between tax benefit from debt and the cost of bankruptcy. Under this hypothesis, split rated firms should issue less debt to avoid the costly borrowing cost arising from split ratings. On the other hand, the pecking order theory suggests that firms' choices of financing sources depend on the sources' level of adverse selections. Under this hypothesis, split rated firms should rely more on debt financing because split ratings further exacerbate firms' current information asymmetry/adverse selection problems. In addition, the market-timing theory also suggests that firms with split ratings should issue more debt because the capital market is more favourable than the equity market (the magnitude of the cost of equity arising from split ratings is higher than that of the cost of debt). This Chapter investigates the merit of these capital structure theories.

Table 5.13 provides a brief summary of the empirical findings in this Chapter. This Chapter reveals that split rated firms are, on average, more likely to have a higher level of leverage than their non-split rated peers, and that this effect is consistent across different estimation approaches. One-notch split rated firms have about 1.5% higher market debt ratios than non-split rated firms. The results are mainly revealed in larger firms and those with investment-grade ratings. The probable reason for this behaviour of split rated firms is that CRAs' different opinions about firms' creditworthiness is a signal of information opacity and the information asymmetry problems between firms and investors. Firms with greater exposure to equity financing suffer more from the information asymmetry problem (adverse selection problem) due to an increased cost of equity. Thus, split rated firms prefer issuing debt than equity to avoid or mitigate this problem. This evidence is also consistent with the findings of Petacchi (2015), which suggest that when facing a higher cost of equity, firm managers rely more on debt than equity. The results further suggest that firms' managers attach more emphasis on the information asymmetry and adverse selection problems than on the increased cost of debt arising from split ratings when deciding the optimal leverage target. The higher leverage ratios of split rated firms also suggest that managers are less worried about potential rating downgrades arising from higher leverage, but more concerned about potential rating downgrades and information asymmetry arising from split ratings.

The study also finds that the effect of superior Moody's ratings on capital structure is not significantly different from that of superior S&P ratings. This finding suggests that firms do not differentiate between split ratings with superior Moody's ratings and split ratings with superior S&P ratings when assessing optimal debt level. This finding is in contrast with those of Livingston et al. (2010), Chapter 3 and Chapter 4. This shows that investors' behaviour and firms' behaviour are different when it comes to superior ratings from a given CRA.

To address any concerns about potential endogeneity, propensity score matching (PSM) tests are conducted. The matching methods used include NN matching, radius matching and kernel matching. The results from PSM are consistent with the baseline model. Furthermore, two different models, Tobit and GLM model, are estimated to address any concerns about ratio dependent variables, and consistent results are obtained. Overall, the robustness tests confirm that the baseline results robust using different definitions of capital structure, different measure of split ratings, and different econometric modelling approaches.

The empirical findings of this Chapter offer novel contributions to the existing literature on capital structure and credit ratings. First, the findings fill in a vital gap in the literature that no prior study has investigated, which is the impact of CRAs disagreements about firms' creditworthiness on firms' behaviour regarding capital structure. Because split ratings have a significant impact on leverage, ratings from both CRAs are matter to firm managers when considering capital structure. In addition, the empirical findings also offer strong support to the information asymmetry hypothesis that firms with high information asymmetry problems are more likely to rely more on debt than non-split rated firms.

Second, although the credit ratings are already considered to be a very important determinant of capital structure in various number of studies (e.g. Custódio et al., 2013; Gopalan et al., 2014; Keefe and Yaghoubi, 2016), the significant impact of split ratings on capital structure indicates that the disagreement between CRAs are also a key determinant to firms' capital structure decisions. Thus, the findings add to the knowledge of existing capital structure literature.

Third, the empirical findings of this chapter also offer some practical implications as they have potential impacts on firms' investment and financial policies. Previous literature shows that firms are more likely to issue less debt when they are in the boundary of getting upgraded or downgraded (Kigsen, 2006), firms with split ratings have higher probability of getting rating actions from CRAs in the futures (Livingston et al., 2008), and firms with a greater exposure to rollover risk have higher chances of being downgraded (Gopalan et al., 2014). Thus, split rated firms could potentially affect their future ratings to get a favourable outcome by altering their capital structure to lower level of leverage to avoid the refinancing risks.

Overall, the empirical findings of this Chapter offer strong support to the hypotheses that rating differences between CRAs have a significant impact on firms' capital structure decisions. Firms with split ratings are more likely to rely more on debt and to issue more long-term debt than non-split rated firms.

Table 5.1. Variable Definitions

Variable	Definition	Construction	Data Sources
MDR1	Ratio of total liabilities to market value of assets	$MDR1 = \frac{lt}{(at - ceq) + csho * prcc\_f}$	Compustat
MDR2	Ratio of total debt to total debt plus market value of equity	$MDR2 = \frac{dltt + dlc}{dltt + dlc + csho * prcc\_f}$	Compustat
MDR3	Ratio of long-term debt to long-term debt plus market value of equity	$MDR3 = \frac{dltt}{dltt + csho * prcc\_f}$	Compustat
BDR1	Ratio of total liabilities to total assets	$BDR1 = \frac{lt}{at}$	Compustat
BDR2	Ratio of total debt to total debt plus common equity	$BDR2 = \frac{dltt + dlc}{dltt + dlc + ceq}$	Compustat
BDR3	Ratio of long-term debt to long-term debt plus common equity	$BDR3 = \frac{dltt}{dlt + ceq}$	Compustat
ASPLIT	Absolute split ratings are the rounded average of absolute daily differences between Moody's and S&P over a fiscal year. More than 4-CCR unit *ASPLIT* is set to be 4.	|Moody's rating – S&P rating|	Moody's website and Capital IQ
SPLIT	Split ratings are the average of daily differences between Moody's and S&P over a fiscal year.	(Moody's rating – S&P rating)	Moody's website and Capital IQ
SUP_MOODY	*SUP_MOODY* is a dummy variable, taking the value of 1 if *SPLIT* > 0 (Moody's rating is superior to S&P), and 0 otherwise.	*SUP_MOODY* = 1 if *SPLIT* > 0 *SUP_MOODY* = 0 if *SPLIT* <= 0	Moody's website and Capital IQ
SUP_S&P	*SUP_S&P* is a dummy variable, taking the value of 1 if *SPLIT* < 0 (S&P rating is superior to Moody's rating), and 0 otherwise.	*SUP_S&P* = 1 if *SPLIT* < 0 *SUP_S&P* = 0 if *SPLIT* >= 0	Moody's website and Capital IQ
MOODY_DOWN	*MOODY_DOWN* is a dummy variable, which equals to 1 if a firm's rating is downgraded by Moody's, and 0 otherwise	*MOODY_DOWN* = 1 if downgraded *MOODY_DOWN* = 0 if upgraded or unchanged	Moody's website and Capital IQ
S&P_DOWN_1N	*A* dummy variable, which equals to 1 if a firm's rating is downgraded at least 1 notch by S&P, and 0 otherwise	*S&P_DOWN* = 1 if downgraded by at least 1 notch *S&P_DOWN* = 0 if upgraded or unchanged	Moody's website and Capital IQ
MOODY_DOWN_1N	*A* dummy variable, which equals to 1 if a firm's rating is downgraded at least 1 notch by Moody's, and 0 otherwise	*MOODY_DOWN* = 1 if downgraded by at least 1 notch *MOODY_DOWN* = 0 if upgraded or unchanged	Moody's website and Capital IQ
S&P_DOWN	*S&P_DOWN* is a dummy variable, which equals to 1 if a firm's rating is downgraded by S&P, and 0 otherwise	*S&P_DOWN* = 1 if downgraded *S&P_DOWN* = 0 if upgraded or unchanged	Moody's website and Capital IQ

Table 5.1. Continued.

Variable	Definition	Construction	Data Sources
SPLIT_DUM	Split dummy variable, which equals to 1 if a firm receive split ratings between Moody's and S&P, and 0 otherwise.	*SPLIT_DUM* = 1 if *ASPLIT > 0* *SPLIT_DUM* = 0 if *ASPLIT = 0*	Moody's website and Capital IQ
ASPLIT_R	*ASPLIT_R* is estimated as the average of absolute daily differences between Moody's and S&P over a fiscal year and then only temporary split (*ASPLIT_R* < 0.5) is rounded to 0. More than 4-CCR unit *ASPLIT_R* is set to be 4.	|Moody's rating – S&P rating|	Moody's website and Capital IQ
AGE	Firm age is the natural logarithm of the number of years that the firm has been operating since the founding year.	ln(current year – founding year)	Capital IQ
BETA	Firm systematic risk	*BETA* is estimated using monthly returns over the last 5 years.[77]	Compustat
CASH	The ratio of book value of cash and marketable securities to the book value of total assets.	$\frac{che}{at}$	Compustat
D2A	The ratio of total debt to total assets.	$\frac{dlc + dltt}{at}$	Compustat
EI	Equity issue is the split-adjusted change in shares outstanding times the split-adjusted average stock price dividend by the end of year *t – 1* total assets (Lemmon et al., 2008).	$EI_{i,t} = [csho_t - csho_{t-1} \times (ajex_{t-1}/ajex_t)] \times [prccf_t + prccf_{t-1} \times (ajex_t/ajex_{t-1})]/at$	Compustat
FS	Firm size is the natural log of total assets (Díaz-Díaz et al., 2016; Huang et al., 2016; Ben-Nasr et al., 2015).	*ln(at)*	Compustat
IDIO	The standard deviation of the prior year's monthly returns.	The SD of firms' past year's monthly returns[78]	Compustat
INDFL	The median industry leverage of the sector which a firm is classified by 4-digit SIC code.	The median of industry leverage	Compustat
MTB	Market to book ratio is the ratio of market value of asset to total assets (Huang et al., 2016; González, 2015; Ben-Nasr et al., 2015).	$\frac{MVA}{at}$[79]	Compustat
PROFIT	Profitability of a firm (Frank and Goyal, 2009).	$\frac{oibdp}{at}$	Compustat
R&D	Ratio of R&D expenses to sale. (Keefe and Yaghoubi, 2016)	$ln(1 + [xrd/sale])$	Compustat

[77] *BETA* could be obtained from Compustat database by creating two custom concepts: total monthly return; *TRT1M* = (((*prccm***trfm*)/(*prccm***trfm*)[-1])-1)*100; and *BETA* = (@PCOR(TRT1M,"I0003":TRT1M,-59,0)*@PSTD(TRT1M,-59,0))/(@PSTD("I0003":TRT1M,-59,0)).

[78] *IDIO* could be obtained from Compustat database by creating a concept: IDIO = @PSTD(TRT1M,-12,0).

[79] *MVA = dlc + dltt + ppstkl + csho*prcc_f – txditc*. Details of Compustat items can be found in the Appendix 5.A.

Table 5.1. Continued.

TANG	Firms' assets tangibility (Lemmon et al., 2008; Kirch and Terra, 2012).	$\frac{ppent}{at}$	Compustat
TAXES	The ratio of tax expenditure to book value of total assets.	$\frac{txt}{at}$	Compustat
LEVEL	Set of 19 dummy variables represent the rating categories of a firm calculated as the rounded average of annual average of Moody's and S&P daily ratings	Rounded value of ([Moody_Rating + S&P_Rating]/2)	Moody's website and Capital IQ
*YEAR*INDUSTRY*	Interactions between two dummy groups, *YEAR* and *INDUSTRY*, to control for the macro-economic changes.	*YEAR*: is a set of dummy variables equal to 1 for the given year and 0, otherwise. *INDUSTRY*: is a set of dummy variables for 1-digit SIC industries.[80]	Compustat

Note:Table 5.1 provides the definitions of all used variables and data sources.

[80] 1-digit SIC industry dummies are used to persevere the degree of freedom as the interactions between *YEAR* and *INDUSTRY* increase the number of variables used exponentially. However, robustness tests estimating Eq. (4.1) with 2-digit SIC industry and 3-digit SIC industry dummies produce similar results.

Table 5.2. Sampling process

Filter	Criterion	# of Firm-Years	# of Unique Firms
1	All rated U.S. firms available in Compustat	9,409	1,404
		-41	-5
2	Remove firms involving in major merger/acquisition	9,368	1,399
		-592	-24
3	Remove any observations with negative common/ordinary equity	8,776	1,375
		-1,137	-346
4	Remove any missing dependent variables	7,639	1,029
		-1,031	-145
6	Remove any missing control variables.	6,684	888
		-0	-0
7	Winsorize dependent variables and control variables at 0.5^{th} and 99.5^{th} percentile (except *INDFL* and *ASPLIT*).[81]	6,684	888
Final sample		6,684	888

Table 5.2 details the sample selection procedure of all rated U.S. corporations. The initial sample includes all corporations available in the Compustat database. The initial sample consists of 1,404 firms with 9,409 firm-years and the final sample consist of 888 firms and 6,684 firm-years.

[81] *INDFL* and *ASPLIT* are not winsorized as *INDFL* values are the same for firms in a particular industry in a given year, and *ASPLIT* do not contain any outliers.

Table 5.3. Summary statistics

Variables	N	Mean	SD	Min	Max	p1	p25	p50	p75	p99
MDR1	6,684	0.45	0.19	0.07	0.94	0.09	0.31	0.43	0.58	0.90
BDR1	6,684	0.62	0.15	0.22	0.98	0.26	0.52	0.62	0.73	0.97
MDR2	6,684	0.31	0.20	0.00	0.92	0.00	0.16	0.27	0.42	0.88
BDR2	6,684	0.46	0.21	0.00	0.98	0.01	0.32	0.45	0.59	0.97
MDR3	6,684	0.29	0.20	0.00	0.91	0.00	0.14	0.25	0.40	0.87
BDR3	6,684	0.44	0.21	0.00	0.98	0.00	0.29	0.42	0.57	0.96
TANG	6,684	0.36	0.25	0.02	0.93	0.02	0.15	0.30	0.58	0.91
FS	6,684	8.47	1.38	5.32	12.17	5.70	7.47	8.35	9.43	11.87
MTB	6,684	1.23	0.68	0.34	4.70	0.40	0.78	1.05	1.47	4.02
PROFIT	6,684	0.13	0.06	-0.09	0.36	-0.02	0.09	0.12	0.17	0.32
RD	6,684	0.02	0.04	0.00	0.25	0.00	0.00	0.00	0.01	0.20
EI	6,684	-0.02	0.50	-3.65	2.23	-2.57	-0.03	0.00	0.03	1.53
AGE	6,684	3.81	0.95	0.00	5.89	1.10	3.14	4.01	4.60	5.28
INDFL	6,684	0.46	0.20	0.09	0.92	0.10	0.31	0.43	0.59	0.90
CASH	6,684	0.08	0.09	0.00	0.50	0.00	0.02	0.05	0.12	0.44
D2A	6,684	0.32	0.16	0.00	0.85	0.01	0.20	0.30	0.41	0.76
IDIO	6,656	9.50	6.39	2.33	47.91	2.59	5.55	7.84	11.39	37.07
TAXES	6,498	0.02	0.03	-0.10	0.11	-0.06	0.01	0.02	0.03	0.09
ASPLIT	6,684	1.81	1.49	0.00	4.00	0.00	0.00	2.00	3.00	4.00
SUP_MOODY	6,684	0.20	0.40	0.00	1.00	0.00	0.00	0.00	0.00	1.00
SUP_S&P	6,684	0.48	0.50	0.00	1.00	0.00	0.00	0.00	1.00	1.00
No. of firms	888									

Table 5.3 shows the summary statistics for the rated U.S. corporation from 2003 to 2015. Most variables are winsorized at 0.5^{th} and 99.5^{th} percentile (except for *ASPLIT* and *INDFL*) before summary statistics are calculated. *ASPLIT* is the rounded absolute split ratings calculated by taking the average of daily rating differences over firms' fiscal year and any split higher than 4 CCR units is rounded to 4 CCR unit split.

Table 5.4. Pairwise correlations

	ASPLIT	*TANG*	*FS*	*MTB*	*PROFIT*	*RD*	*EI*	*AGE*	*INDFL*
ASPLIT	1								
TANG	0.0022	1							
FS	-0.2061***	0.0132	1						
MTB	-0.0299**	-0.1735***	0.0015	1					
PROFIT	-0.0861***	0.012	0.0206*	0.5577***	1				
RD	0.027**	-0.3234***	0.1302***	0.2796***	0.0249**	1			
EI	0.0399***	0.0460***	-0.0493***	-0.1670***	-0.2297***	0.0221*	1		
AGE	-0.0643***	-0.1466***	0.2380***	0.0121	0.0829***	-0.005	-0.1076***	1	
INDFL	0.0159	0.3087***	0.0816***	-0.4158***	-0.2454***	-0.3926***	0.0426***	0.0781***	1

Table 5.4 shows the pairwise correlations between explanatory variables. ***, **, and * refer to significant coefficients at the 1%, 5%, 10% levels.

Table 5.5. Statistical properties and distributions of annual split ratings

	No. of obs.	Mean	SD	Min	Max	1 CCR (%)	2 CCR (%)	3 CCR (%)	4 CCR (%)	5 CCR (%)	6 CCR (%)	7 CCR 9 CCR (%)	10 CCR 12 CCR (%)	>= 13 CCR (%)	Split total (%)
Panel A. Absolute split ratings															
Absolute split ratings	6,684	2.120	2.177	0	19	17.4	14.1	22.0	5.4	3.6	5.0	2.5	0.6	0.2	70.9
Panel B. Split ratings															
Moody's – S&P	6,684	-1.126	2.775	-17	19	16.7	13.2	21.3	5.3	3.5	5.0	2.5	0.6	0.2	68.3
Moody's > S&P	1,326	2.330	1.726	1	19	38.5	20.6	29.6	5.3	2.1	1.7	1.7	0.2	0.3	19.8
S&P > Moody's	3,237	3.280	2.077	1	17	18.8	18.9	31.8	8.7	6.3	9.7	4.4	1.2	0.3	48.4

The table presents the descriptive statistics and the distribution of absolute and annual split ratings between Moody's and S&P. Firms' ratings are transformed into number using 58-point comprehensive credit ratings (CCR) scale. Split ratings are computed as daily CCR differences, averaged over the calendar year for each corporation, and rounded to nearest integers. Similar to annual split ratings, absolute split ratings use absolute daily CCR differences to calculate split ratings. 1 CCR (%), …,7 CCR – 9 CCR (%), 10 CCR – 12 CCR (%), and >=13 CCR (%) columns indicate the magnitudes of split ratings in CCR units. Split total (%) column indicates the percentage of the annual average split ratings to the total number of observations.

Table 5.6. Split Ratings and Capital Structure.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
		(3.58)	(2.40)	(2.67)	(2.22)	(2.39)	(2.10)
$TANG_{t-1}$	+	0.050***	0.040**	0.115***	0.127***	0.130***	0.147***
		(3.01)	(1.99)	(5.15)	(4.89)	(6.00)	(5.63)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.029***	0.018***	0.030***
		(7.70)	(7.14)	(4.75)	(5.63)	(4.91)	(5.73)
MTB_{t-1}	-	-0.111***	0.008	-0.062***	0.034***	-0.058***	0.034***
		(-18.69)	(0.97)	(-10.53)	(3.05)	(-9.86)	(3.04)
$PROFIT_{t-1}$	-	-0.169***	0.032	-0.197***	0.011	-0.160**	0.060
		(-3.23)	(0.48)	(-3.11)	(0.13)	(-2.53)	(0.68)
RD_{t-1}	-	-0.296***	-0.476***	-0.210**	-0.407***	-0.203**	-0.408***
		(-3.37)	(-3.71)	(-2.27)	(-2.81)	(-2.19)	(-2.83)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.000	0.008
		(-2.37)	(-1.54)	(-0.70)	(0.81)	(-0.12)	(1.49)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.48)	(2.68)	(0.25)	(0.91)	(0.77)	(1.15)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.176***
		(9.19)	(8.37)	(6.21)	(6.47)	(5.72)	(5.86)
Constant		0.004	-0.085	-0.226	-0.438**	-0.253	-0.476**
		(0.02)	(-0.42)	(-1.39)	(-2.04)	(-1.58)	(-2.22)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.599	0.246	0.509	0.304	0.503	0.311
No. of firms		888	888	888	888	888	888

Note: Table 5.6 reports the results of Eq. (5.1) using the OLS approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time *t – 1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.7. Large firms and small firms.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times SMALL_{t-1}$	+	0.002	0.003	0.001	0.003	-0.000	0.002
		(0.85)	(1.10)	(0.33)	(0.82)	(-0.18)	(0.49)
$ASPLIT_{t-1} \times (1\text{-}SMALL_{t-1})$	+	0.009***	0.007***	0.009***	0.009***	0.009***	0.010***
		(5.22)	(2.72)	(4.15)	(2.64)	(4.33)	(2.80)
$TANG_{t-1}$	+	0.050***	0.040**	0.115***	0.127***	0.130***	0.147***
		(3.02)	(1.99)	(5.14)	(4.88)	(5.99)	(5.62)
FS_{t-1}	+	0.020***	0.026***	0.014***	0.026***	0.013***	0.025***
		(5.71)	(5.81)	(3.25)	(4.43)	(3.20)	(4.39)
MTB_{t-1}	-	-0.112***	0.008	-0.063***	0.033***	-0.059***	0.033***
		(-18.89)	(0.93)	(-10.68)	(3.01)	(-10.03)	(2.98)
$PROFIT_{t-1}$	-	-0.164***	0.035	-0.191***	0.015	-0.153**	0.065
		(-3.15)	(0.52)	(-3.03)	(0.18)	(-2.44)	(0.74)
RD_{t-1}	-	-0.305***	-0.481***	-0.220**	-0.414***	-0.215**	-0.417***
		(-3.50)	(-3.75)	(-2.40)	(-2.86)	(-2.34)	(-2.90)
EI_{t-1}	-	-0.008**	-0.006	-0.003	0.004	-0.001	0.007
		(-2.47)	(-1.59)	(-0.81)	(0.75)	(-0.26)	(1.41)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.47)	(2.67)	(0.24)	(0.90)	(0.76)	(1.15)
$INDFL_{t-1}$	+	0.170***	0.190***	0.149***	0.196***	0.127***	0.174***
		(9.09)	(8.32)	(6.10)	(6.41)	(5.62)	(5.80)
Constant		0.041	-0.063	-0.185	-0.406*	-0.205	-0.436**
		(0.25)	(-0.31)	(-1.15)	(-1.91)	(-1.31)	(-2.06)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.600	0.246	0.511	0.305	0.505	0.312
No. of firms		888	888	888	888	888	888
ΔCOEF		-0.007***	-0.004	-0.008***	-0.006	-0.009***	-0.008*
		(9.41)	(1.62)	(7.70)	(2.08)	(11.55)	(3.31)

Note: Table 5.7 reports the results of Eq. (5.1) using the OLS approach with two interaction term, $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$, where $SMALL_{t-1}$ is a dummy that identifies firms with below-sample-median value of firm size (*FS*). The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. The tests of the differences between two interaction terms are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (F-test for ΔCOEF). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.8. Investment-grade firms and speculative-grade firms.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times INVST_{t-1}$	+	0.009***	0.007**	0.009***	0.008**	0.009***	0.008**
		(4.61)	(2.07)	(3.77)	(1.96)	(3.95)	(2.04)
$ASPLIT_{t-1} \times (1- INVST_{t-1})$	+	0.003	0.004	0.002	0.005	0.001	0.004
		(1.24)	(1.46)	(0.81)	(1.33)	(0.45)	(1.11)
$TANG_{t-1}$	+	0.050***	0.040**	0.115***	0.127***	0.130***	0.147***
		(3.02)	(2.00)	(5.16)	(4.89)	(6.02)	(5.63)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.030***	0.019***	0.030***
		(7.78)	(7.16)	(4.81)	(5.65)	(4.98)	(5.76)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.034***	-0.058***	0.034***
		(-18.78)	(0.96)	(-10.59)	(3.04)	(-9.93)	(3.03)
$PROFIT_{t-1}$	-	-0.165***	0.034	-0.193***	0.013	-0.155**	0.062
		(-3.17)	(0.51)	(-3.06)	(0.15)	(-2.47)	(0.71)
RD_{t-1}	-	-0.303***	-0.479***	-0.217**	-0.410***	-0.211**	-0.412***
		(-3.47)	(-3.72)	(-2.36)	(-2.83)	(-2.29)	(-2.85)
EI_{t-1}	-	-0.008**	-0.006	-0.003	0.004	-0.001	0.008
		(-2.45)	(-1.57)	(-0.77)	(0.78)	(-0.20)	(1.46)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.54)	(2.70)	(0.29)	(0.92)	(0.82)	(1.17)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.176***
		(9.17)	(8.35)	(6.19)	(6.46)	(5.70)	(5.84)
Constant		0.010	-0.082	-0.221	-0.435**	-0.247	-0.472**
		(0.06)	(-0.40)	(-1.35)	(-2.03)	(-1.54)	(-2.21)
ΔCOEF		0.006**	0.003	0.007*	0.003	0.008**	0.004
		(5.47)	(0.57)	(3.42)	(0.34)	(4.65)	(0.59)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.600	0.246	0.510	0.304	0.504	0.311
No. of firms		888	888	888	888	888	888

Note: Table 5.8 reports the results of Eq. (5.1) using the OLS approach with two interaction term, $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$, where $INVST_{t-1}$ is a dummy that identifies firms with an investment-grade rating. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. The tests of the differences between two interaction terms are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (F-test for ΔCOEF). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.9. Crisis and non-crisis period.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times CRISIS_{t-1}$	+	0.010***	0.005	0.011***	0.007	0.011***	0.008
		(3.19)	(1.45)	(2.84)	(1.41)	(2.71)	(1.53)
$ASPLIT_{t-1} \times (1- CRISIS_{t-1})$	+	0.005***	0.005**	0.004**	0.006**	0.003*	0.005*
		(3.02)	(2.36)	(2.08)	(2.11)	(1.82)	(1.94)
$TANG_{t-1}$	+	0.050***	0.040**	0.115***	0.127***	0.130***	0.147***
		(3.02)	(1.99)	(5.16)	(4.89)	(6.03)	(5.63)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.029***	0.018***	0.030***
		(7.69)	(7.14)	(4.74)	(5.63)	(4.89)	(5.72)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.034***	-0.058***	0.034***
		(-18.69)	(0.97)	(-10.55)	(3.05)	(-9.88)	(3.03)
$PROFIT_{t-1}$	-	-0.168***	0.032	-0.196***	0.011	-0.159**	0.060
		(-3.22)	(0.48)	(-3.10)	(0.13)	(-2.52)	(0.68)
RD_{t-1}	-	-0.297***	-0.476***	-0.210**	-0.407***	-0.204**	-0.408***
		(-3.38)	(-3.71)	(-2.28)	(-2.81)	(-2.20)	(-2.83)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.000	0.008
		(-2.36)	(-1.54)	(-0.69)	(0.81)	(-0.12)	(1.49)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.49)	(2.68)	(0.26)	(0.91)	(0.78)	(1.16)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.176***
		(9.18)	(8.38)	(6.19)	(6.47)	(5.71)	(5.85)
Constant		0.006	-0.085	-0.224	-0.437**	-0.251	-0.475**
		(0.04)	(-0.42)	(-1.37)	(-2.04)	(-1.57)	(-2.22)
ΔCOEF		0.005*	0.000	0.007*	0.001	0.008*	0.003
		(2.89)	(0.01)	(3.62)	(0.07)	(3.74)	(0.25)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.599	0.246	0.510	0.304	0.504	0.311
No. of firms		888	888	888	888	888	888

Note: Table 5.9 reports the results of Eq. (5.1) using the OLS approach with two interaction term, $ASPLIT_{t-1} \times CRISIS_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$, where $CRISIS_{t-1}$ is a dummy that identifies the crisis period (2007 – 2009). The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. The tests of the differences between two interaction terms are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (F-test for ΔCOEF). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.10. Matching quality tests for NN matching without replacement and the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched / Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|
$IDIO_{t-1}$	U	9.728	7.933	32.5		9.45	0.000
	M	7.929	8.055	-2.3	93.0	-0.74	0.458
$TAXES_{-1}$	U	0.018	0.027	-32.7		-10.5	0.000
	M	0.026	0.026	0.5	98.4	0.13	0.893
$CASH_{-1}$	U	0.082	0.093	-11.6		-3.89	0.000
	M	0.090	0.090	-0.7	94.2	-0.17	0.868
FS_{t-1}	U	8.368	8.851	-35.6		-11.38	0.000
	M	8.726	8.758	-2.3	93.5	-0.60	0.550
MTB_{t-1}	U	1.204	1.359	-22.1		-7.32	0.000
	M	1.349	1.339	1.5	93.3	0.34	0.734
$TANG_{t-1}$	U	0.366	0.350	6.5		2.12	0.034
	M	0.357	0.353	1.9	70.6	0.48	0.634

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
MDR1	Unmatched	0.459	0.394	0.065	0.006	11.38***
	ATT	0.414	0.400	0.015	0.007	2.13**
BDR1	Unmatched	0.631	0.592	0.039	0.005	8.08***
	ATT	0.612	0.594	0.018	0.006	2.87**
MDR2	Unmatched	0.320	0.247	0.072	0.006	11.91***
	ATT	0.269	0.255	0.014	0.007	2.02**
BDR2	Unmatched	0.474	0.410	0.064	0.006	9.85***
	ATT	0.442	0.419	0.024	0.008	2.9***
MDR3	Unmatched	0.300	0.229	0.071	0.006	11.86***
	ATT	0.251	0.236	0.015	0.007	2.08**
BDR3	Unmatched	0.448	0.383	0.065	0.007	9.86***
	ATT	0.417	0.392	0.024	0.008	2.97***

Panel C. Pseudo R-square test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.108	695.36	0	6.2	3.8	83.0*	0.88	67
Matched	0.011	36.57	1	1.7	1.4	24.4	0.84	33

Note: Table 5.10 shows various matching quality tests for the NN matching without replacement. Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the $SPLIT\_DUM_{t-1}$ variable, which equals one if firms are split rated at time *t – 1* and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), idiosyncratic risk (*IDIO*), asset tangibility (*TANG*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R-square and the joint-significance tests.

Table 5.11. OLS regression using the PSM sample (NN matching without replacement).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.008***	0.008***	0.011***	0.008***	0.011***
		(3.90)	(2.60)	(3.54)	(3.03)	(3.69)	(3.21)
$TANG_{t-1}$	-0.035	0.075***	0.067***	0.142***	0.154***	0.152***	0.167***
	(-0.33)	(3.53)	(2.65)	(5.55)	(4.78)	(6.09)	(5.24)
FS_{t-1}	0.010	0.025***	0.032***	0.020***	0.034***	0.017***	0.032***
	(0.27)	(6.14)	(5.96)	(3.88)	(4.79)	(3.81)	(4.76)
MTB_{t-1}	0.010	-0.087***	0.033***	-0.039***	0.068***	-0.037***	0.065***
	(0.27)	(-12.34)	(3.21)	(-5.92)	(5.09)	(-5.95)	(4.94)
$PROFIT_{t-1}$		-0.148**	0.103	-0.202**	0.078	-0.161**	0.137
		(-2.13)	(1.14)	(-2.56)	(0.66)	(-2.09)	(1.17)
RD_{t-1}		-0.200*	-0.561***	-0.178*	-0.639***	-0.173*	-0.642***
		(-1.88)	(-3.28)	(-1.75)	(-3.25)	(-1.72)	(-3.38)
EI_{t-1}		-0.008*	-0.007	-0.002	0.003	-0.001	0.005
		(-1.81)	(-1.27)	(-0.44)	(0.43)	(-0.29)	(0.74)
AGE_{t-1}		0.009**	0.018***	0.004	0.013*	0.005	0.013**
		(2.40)	(3.06)	(0.89)	(1.89)	(1.16)	(2.00)
$INDFL_{t-1}$		0.200***	0.224***	0.158***	0.221***	0.131***	0.195***
		(8.81)	(7.95)	(5.64)	(6.15)	(4.86)	(5.56)
$IDIO_{t-1}$	0.020***						
	(3.74)						
$TAXES_{-1}$	-4.673***						
	(-4.98)						
$CASH_{-1}$	-0.247						
	(-1.04)						
Constant	-0.745	0.297***	0.384***	0.122	0.206	0.132	0.218*
	(-1.14)	(3.59)	(4.32)	(1.13)	(1.59)	(1.25)	(1.73)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,345	2,480	2,480	2,480	2,480	2,480	2,480
Pseudo R-squared	0.108						
Adjusted R-squared		0.634	0.283	0.549	0.332	0.553	0.341
No. of firms		655	655	655	655	655	655

Note: Table 5.11 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the OLS approach with a matched sample. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.12. Superior S&P ratings versus Superior Moody's ratings.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
SUP_MOODY_{t-1}	+	0.025***	0.026***	0.020***	0.025**	0.017**	0.021**
		(4.36)	(3.37)	(2.85)	(2.58)	(2.49)	(2.12)
$SUP\_S\&P_{t-1}$	+	0.016***	0.020***	0.017***	0.024***	0.016***	0.024***
		(3.59)	(3.14)	(3.09)	(3.05)	(3.07)	(3.10)
$TANG_{t-1}$	+	0.050***	0.040**	0.115***	0.127***	0.130***	0.147***
		(3.01)	(1.99)	(5.17)	(4.90)	(6.02)	(5.64)
FS_{t-1}	+	0.023***	0.028***	0.019***	0.029***	0.018***	0.030***
		(7.68)	(7.12)	(4.73)	(5.62)	(4.89)	(5.71)
MTB_{t-1}	-	-0.111***	0.008	-0.062***	0.034***	-0.058***	0.034***
		(-18.71)	(1.00)	(-10.53)	(3.08)	(-9.85)	(3.06)
$PROFIT_{t-1}$	-	-0.166***	0.035	-0.195***	0.013	-0.159**	0.061
		(-3.19)	(0.53)	(-3.09)	(0.15)	(-2.51)	(0.69)
RD_{t-1}	-	-0.287***	-0.470***	-0.203**	-0.400***	-0.198**	-0.402***
		(-3.24)	(-3.68)	(-2.19)	(-2.77)	(-2.13)	(-2.80)
EI_{t-1}	-	-0.008**	-0.006	-0.003	0.004	-0.001	0.008
		(-2.47)	(-1.62)	(-0.76)	(0.76)	(-0.17)	(1.46)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.45)	(2.65)	(0.23)	(0.89)	(0.76)	(1.14)
$INDFL_{t-1}$	+	0.172***	0.191***	0.152***	0.198***	0.130***	0.176***
		(9.20)	(8.37)	(6.21)	(6.47)	(5.72)	(5.85)
Constant		0.005	-0.087	-0.225	-0.438**	-0.253	-0.476**
		(0.03)	(-0.45)	(-1.44)	(-2.13)	(-1.64)	(-2.31)
ΔCOEF		0.009	0.006	0.003	0.001	0.001	-0.003
		(2.14)	(0.66)	(0.20)	(0.03)	(0.01)	(0.06)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.600	0.248	0.510	0.305	0.504	0.312
No. of firms		888	888	888	888	888	888

Note: Table 5.12 reports the results of Eq. (5.1) using the OLS approach with two interaction term, $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$. The main independent variables are *SUP_MOODY* and *SUP_S&P*, where *SUP_MOODY* (*SUP_S&P*) is a dummy variable equal to 1 if Moody's (S&P) rating is higher. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. The tests of the differences between two interaction terms are presented on the row titled ΔCOEF. Numbers in parentheses are robust t-statistics (F-test for ΔCOEF). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.13. Summary of Chapter 5 key findings.

Research questions	Equations, hypotheses and tables	Findings
What is the impact of split ratings on firms' capital structure decisions?	Hypothesis 1 Equation (5.1) Table 5.6	Split rated firms have a higher level of leverage than non-split rated firms with similar credit risk. Firms with one-notch split have about 1.5% higher market debt ratios than non-split rated firms with similar credit risk. This suggests that split ratings are indeed a signal of information asymmetry and that firms with a greater information asymmetry problem rely more on debt financing than equity financing.
Is the impact of superior ratings from Moody's on firms' capital structure decisions different from the impact of superior ratings from S&P?	Hypothesis 2 Equation (5.2) Table 5.12	The impact of superior Moody's ratings is not significantly different from that of superior S&P ratings, suggesting that firms' managers do not differentiate between Moody's and S&P when assessing the consequences of split ratings for capital structure.
Cross-sectional tests	Small vs large firms, Tables 5.7, 5.B.3 and 5.B.4. Investment-grade vs speculative-grade firms, Tables 5.8, 5.B.5 and 5.B.6 Crisis vs non-crisis periods Tables 5.9, 5.B.7 and 5.B.8.	The effect of split ratings on firms' level of capital structure is predominantly associated with large firms and investment-grade firms. The effect of split ratings on firms' level of long-term debt is strong during both the crisis period and the non-crisis period.
Endogeneity investigation	PSM with various matching methods Tables 5.10, 5.11, 5.B.11, 5.B.12, 5.B.13, 5.B.14, 5.B.15, 5.B.16, 5.B.17, 5.B.18, 5.B.19, 5.B.2.0, 5.B.21 and 5.B.22.	The results from PSM with various matching methods are very similar to the baseline results. By the nature of the matching methods, the effect of information asymmetry arising from split ratings is separated from other sources of information asymmetry through the use of PSM.
Additional robustness tests	Different definition of split ratings, Tables 5.B.23, 5.B.24, 5.B.25, 5.B.26, 5.B.27 and 5.B.28 Excluding missing accounting variables, Tables 5.B.29, 5.B.30 and 5.B.31 Excluding financial firms and/or utility firms. Tables 5.B.32, 5.B.33 and 5.B.34.	The results and inference from various robustness tests are consistent with the main results.

Appendix 5.A: Compustat variable definitions

Compustat item	Definition
ajex	Adjustment factor (cumulative) by ex-date, a ratio which enables you to adjust per-share data (price, earnings per share, dividends per share), as well as share data (shares outstanding and shares traded) for all stock splits and stock dividends that occur subsequent to the end of a given period.
at	Total assets, the total assets/liabilities of a company at a point in time.
ceq	Total common equity, this item represents the common shareholders' interest in the company.
che	Cash and short-term investment, cash and all securities readily transferable to cash as listed in the current asset section.
csho	Common shares outstanding, represents the net number of all common shares outstanding at year-end for the annual file, and as of the Balance Sheet date for the quarterly file excluding treasury shares and scrip.
dclo	Debt – capitalized lease obligations, represents the debt obligation a company incurs when capitalizing leases.
dd	Debt debentures represents long-term debt containing a promise to pay a specific amount of money on a fixed date (usually more than 10 years after issuance – and with a promise to pay interest on stated dates).
dd2 to dd5	Debt - maturing in 2nd, 3rd, 4th, and 5th years, the dollar amount of long-term debt that matures in the second, third, fourth, and fifth years from the Balance Sheet.
dlc	Debt in current liabilities represents the total amount of short-term notes and the current portion of long-term debt that is due in one year.
dltt	Total long-term debt represents debt obligations due more than one year from the company's Balance Sheet date or due after the current operating cycle.
dn	Debt – notes, long-term debt possibly secured by the pledge of property or securities owned by the company.
lt	Total liabilities, current liabilities plus long-term debt plus other liabilities plus deferred taxes and investment tax credit plus minority interest.
oibdp	Operating income before depreciation represents Sales - Net (*sale*) minus cost of goods sold (*cogs*) and selling, general, and administrative expenses (*xsga*) before deducting depreciation, depletion and amortization (*dpact*).
ppent	Total (gross) property, plant and equipment represents the cost of fixed property of a company used in the production of revenue before adjustments for accumulated depreciation, depletion, and amortization.
prccm	Price close monthly.
prcc_f	Price close at the end of the fiscal year.
pstkl	Preferred stock – liquidating value, the total dollar value of the net number of preferred shares outstanding in the event of involuntary liquidation.
sale	Net sales, gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers.
trfm	Monthly total return factor.
txditc	Deferred taxes and investment tax credit, the accumulated differences between income expense for financial statements and tax forms due to timing differences and investment tax credit.
txt	Total income taxes, all income taxes imposed by federal, state and foreign governments.
xrd	Research and development expense represents all costs that relate to the development of new products or services.

Note: The table provides the definitions of all Compustat items used.

Appendix 5.B: Additional robustness test

Table 5.B.1. Split Ratings and Capital Structure using the Tobit approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
		(3.62)	(2.43)	(2.71)	(2.25)	(2.39)	(2.11)
$TANG_{t-1}$	+	0.050***	0.040**	0.116***	0.128***	0.131***	0.148***
		(3.04)	(2.01)	(5.23)	(4.96)	(6.10)	(5.71)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.030***	0.019***	0.030***
		(7.78)	(7.21)	(4.82)	(5.70)	(4.97)	(5.81)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.034***	-0.059***	0.033***
		(-18.89)	(0.98)	(-10.57)	(3.06)	(-9.98)	(2.99)
$PROFIT_{t-1}$	-	-0.169***	0.032	-0.195***	0.012	-0.158**	0.061
		(-3.27)	(0.48)	(-3.10)	(0.14)	(-2.50)	(0.69)
RD_{t-1}	-	-0.296***	-0.476***	-0.223**	-0.418***	-0.218**	-0.422***
		(-3.41)	(-3.75)	(-2.35)	(-2.85)	(-2.28)	(-2.87)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.000	0.008
		(-2.39)	(-1.55)	(-0.64)	(0.82)	(-0.10)	(1.50)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.51)	(2.71)	(0.26)	(0.92)	(0.78)	(1.18)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.177***
		(9.29)	(8.47)	(6.25)	(6.53)	(5.78)	(5.91)
Constant		0.004	-0.085	-0.227	-0.439**	-0.254	-0.478**
		(0.03)	(-0.42)	(-1.41)	(-2.07)	(-1.61)	(-2.26)
$\Delta Y^*/\Delta X$		0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
$\Delta E(Y)/\Delta X$		0.005***	0.005**	0.004***	0.006**	0.004**	0.005**
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.1 reports the results of Eq. (5.1) using the Tobit approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title $\Delta Y^*/\Delta X$ shows the marginal effects on the expected value of the censored outcome while row title $\Delta E(Y)/\Delta X$ shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.2. Split Ratings and Capital Structure using the GLM approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.022***	0.024**	0.024***	0.025**	0.022**	0.024**
		(3.45)	(2.52)	(2.58)	(2.20)	(2.32)	(2.07)
$TANG_{t-1}$	+	0.209***	0.180**	0.555***	0.539***	0.644***	0.629***
		(3.10)	(2.03)	(5.41)	(4.91)	(6.29)	(5.66)
FS_{t-1}	+	0.093***	0.129***	0.082***	0.127***	0.081***	0.129***
		(7.38)	(7.22)	(4.34)	(5.70)	(4.44)	(5.79)
MTB_{t-1}	-	-0.609***	0.038	-0.494***	0.144***	-0.496***	0.147***
		(-22.50)	(1.08)	(-13.69)	(3.07)	(-13.20)	(3.05)
$PROFIT_{t-1}$	-	-0.645***	0.155	-0.981***	0.062	-0.799**	0.280
		(-2.91)	(0.55)	(-3.12)	(0.17)	(-2.45)	(0.74)
RD_{t-1}	-	-1.624***	-1.978***	-1.745***	-1.811***	-1.811***	-1.869***
		(-4.16)	(-3.78)	(-3.19)	(-2.87)	(-3.11)	(-2.88)
EI_{t-1}	-	-0.033**	-0.026	0.007	0.020	0.024	0.036
		(-2.26)	(-1.60)	(0.31)	(0.85)	(1.07)	(1.55)
AGE_{t-1}	+	0.029**	0.051***	-0.001	0.021	0.009	0.028
		(2.28)	(2.74)	(-0.06)	(0.94)	(0.45)	(1.19)
$INDFL_{t-1}$	+	0.665***	0.844***	0.681***	0.829***	0.602***	0.751***
		(8.74)	(8.43)	(5.86)	(6.49)	(5.34)	(5.89)
Constant		-1.979***	-2.562***	-4.497***	-5.134***	-5.008***	-5.649***
		(-2.86)	(-3.10)	(-6.22)	(-6.00)	(-6.98)	(-6.63)
ΔY/ΔX		0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
		(3.45)	(2.52)	(2.58)	(2.20)	(2.32)	(2.07)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.599	0.246	0.509	0.304	0.503	0.311
No. of firms		888	888	888	888	888	888

Note: Table 5.B.2 reports the results of Eq. (5.1) using the GLM approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. Marginal effects of split ratings are presented on row title ΔY/ΔX. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.3. Large firms and small firms with the Tobit approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times SMALL_{t-1}$	+	0.002	0.003	0.001	0.003	-0.000	0.002
		(0.86)	(1.11)	(0.33)	(0.83)	(-0.18)	(0.50)
$ASPLIT_{t-1} \times (1\text{-}SMALL_{t-1})$	+	0.009***	0.007***	0.009***	0.009***	0.009***	0.010***
		(5.28)	(2.75)	(4.22)	(2.68)	(4.31)	(2.81)
$TANG_{t-1}$	+	0.050***	0.040**	0.116***	0.128***	0.131***	0.148***
		(3.05)	(2.02)	(5.22)	(4.96)	(6.09)	(5.70)
FS_{t-1}	+	0.020***	0.026***	0.015***	0.026***	0.013***	0.026***
		(5.77)	(5.87)	(3.30)	(4.49)	(3.25)	(4.46)
MTB_{t-1}	-	-0.112***	0.008	-0.064***	0.033***	-0.060***	0.033***
		(-19.09)	(0.94)	(-10.72)	(3.02)	(-10.14)	(2.94)
$PROFIT_{t-1}$	-	-0.164***	0.035	-0.190***	0.016	-0.152**	0.066
		(-3.18)	(0.53)	(-3.01)	(0.19)	(-2.40)	(0.75)
RD_{t-1}	-	-0.305***	-0.481***	-0.233**	-0.426***	-0.230**	-0.432***
		(-3.54)	(-3.79)	(-2.48)	(-2.90)	(-2.43)	(-2.94)
EI_{t-1}	-	-0.008**	-0.006	-0.003	0.004	-0.001	0.007
		(-2.50)	(-1.61)	(-0.75)	(0.76)	(-0.23)	(1.42)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.50)	(2.70)	(0.24)	(0.91)	(0.77)	(1.17)
$INDFL_{t-1}$	+	0.170***	0.190***	0.149***	0.196***	0.128***	0.175***
		(9.19)	(8.41)	(6.14)	(6.46)	(5.68)	(5.85)
Constant		0.041	-0.063	-0.185	-0.407*	-0.206	-0.438**
		(0.25)	(-0.32)	(-1.17)	(-1.93)	(-1.33)	(-2.09)
$\Delta Y^*/\Delta X(ASPLIT \times SMALL)$		0.002	0.003	0.001	0.003	-0.000	0.002
$\Delta Y^*/\Delta X(ASPLIT \times (1\text{-}SMALL))$		0.009***	0.007***	0.009***	0.009***	0.009***	0.009***
$\Delta E(Y)/\Delta X(ASPLIT \times SMALL)$		0.002	0.003	0.001	0.003	-0.000	0.002
$\Delta E(Y)/\Delta X(ASPLIT \times (1\text{-}SMALL))$		0.009***	0.007***	0.008***	0.009***	0.008***	0.009***
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.3 reports the results of Eq. (5.1) using the Tobit approach with two interaction term, $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$, where $SMALL_{t-1}$ is a dummy that identifies firms with below-sample-median value of firm size (*FS*). The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title $\Delta Y^*/\Delta X$ shows the marginal effects on the expected value of the censored outcome while row title $\Delta E(Y)/\Delta X$ shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.4. Large firms and small firms with the GLM approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times SMALL_{t-1}$	+	0.008	0.014	0.008	0.012	0.003	0.007
		(0.89)	(1.14)	(0.64)	(0.80)	(0.22)	(0.49)
$ASPLIT_{t-1} \times (1\text{-}SMALL_{t-1})$	+	0.038***	0.034***	0.042***	0.039***	0.044***	0.041***
		(4.93)	(2.83)	(3.68)	(2.61)	(3.82)	(2.76)
$TANG_{t-1}$	+	0.209***	0.180**	0.556***	0.539***	0.644***	0.629***
		(3.11)	(2.03)	(5.40)	(4.91)	(6.28)	(5.65)
FS_{t-1}	+	0.078***	0.118***	0.063***	0.113***	0.058***	0.111***
		(5.42)	(5.94)	(2.93)	(4.51)	(2.83)	(4.45)
MTB_{t-1}	-	-0.611***	0.036	-0.496***	0.142***	-0.498***	0.144***
		(-22.73)	(1.03)	(-13.78)	(3.03)	(-13.28)	(2.99)
$PROFIT_{t-1}$	-	-0.625***	0.168	-0.955***	0.080	-0.768**	0.303
		(-2.82)	(0.59)	(-3.04)	(0.22)	(-2.36)	(0.80)
RD_{t-1}	-	-1.656***	-2.003***	-1.781***	-1.842***	-1.853***	-1.909***
		(-4.27)	(-3.82)	(-3.28)	(-2.92)	(-3.20)	(-2.94)
EI_{t-1}	-	-0.035**	-0.027*	0.005	0.018	0.022	0.034
		(-2.34)	(-1.66)	(0.24)	(0.79)	(0.99)	(1.48)
AGE_{t-1}	+	0.029**	0.051***	-0.002	0.021	0.008	0.027
		(2.27)	(2.73)	(-0.08)	(0.93)	(0.42)	(1.18)
$INDFL_{t-1}$	+	0.658***	0.839***	0.671***	0.822***	0.591***	0.742***
		(8.63)	(8.38)	(5.76)	(6.42)	(5.23)	(5.83)
Constant		-1.834***	-2.466***	-4.328***	-5.002***	-4.802***	-5.482***
		(-2.70)	(-3.00)	(-6.08)	(-5.89)	(-6.83)	(-6.50)
$\Delta Y/\Delta X(ASPLIT \times SMALL)$		0.002	0.003	0.002	0.003	0.000	0.002
$\Delta Y/\Delta X(ASPLIT \times (1\text{-}SMALL))$		0.008***	0.008***	0.008***	0.009***	0.008***	0.010***
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.4 reports the results of Eq. (5.1) using the GLM approach with two interaction term, $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times SMALL_{t-1}$ and $ASPLIT_{t-1} \times (1 - SMALL_{t-1})$, where $SMALL_{t-1}$ is a dummy that identifies firms with below-sample-median value of firm size (*FS*). The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Marginal effects of split ratings are presented on row title ΔY/ΔX. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.5. Investment-grade firms and speculative-grade firms with the Tobit approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times INVST_{t-1}$	+	0.009***	0.007**	0.009***	0.008**	0.008***	0.008**
		(4.66)	(2.10)	(3.81)	(1.99)	(3.92)	(2.02)
$ASPLIT_{t-1} \times (1\text{-}INVST_{-1})$	+	0.003	0.004	0.002	0.005	0.001	0.004
		(1.25)	(1.48)	(0.83)	(1.36)	(0.47)	(1.14)
$TANG_{t-1}$	+	0.050***	0.040**	0.116***	0.128***	0.131***	0.148***
		(3.06)	(2.02)	(5.24)	(4.96)	(6.11)	(5.71)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.030***	0.019***	0.030***
		(7.86)	(7.24)	(4.87)	(5.73)	(5.04)	(5.84)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.033***	-0.059***	0.033***
		(-18.98)	(0.97)	(-10.62)	(3.05)	(-10.03)	(2.98)
$PROFIT_{t-1}$	-	-0.165***	0.034	-0.191***	0.014	-0.154**	0.063
		(-3.20)	(0.51)	(-3.05)	(0.16)	(-2.44)	(0.72)
RD_{t-1}	-	-0.303***	-0.479***	-0.230**	-0.422***	-0.226**	-0.426***
		(-3.51)	(-3.76)	(-2.44)	(-2.86)	(-2.39)	(-2.90)
EI_{t-1}	-	-0.008**	-0.006	-0.003	0.004	-0.001	0.008
		(-2.47)	(-1.59)	(-0.71)	(0.80)	(-0.17)	(1.47)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.007
		(2.57)	(2.73)	(0.29)	(0.94)	(0.83)	(1.20)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.177***
		(9.27)	(8.44)	(6.23)	(6.51)	(5.76)	(5.90)
Constant		0.010	-0.082	-0.222	-0.437**	-0.248	-0.474**
		(0.06)	(-0.41)	(-1.37)	(-2.05)	(-1.57)	(-2.24)
ΔY*/ΔX(*ASPLIT* ×*INVST*)		0.009***	0.007**	0.008***	0.008**	0.008***	0.008**
ΔY*/ΔX(*ASPLIT* ×(*1-INVST*))		0.003	0.004	0.002	0.005	0.001	0.004
ΔE(Y)/ΔX(*ASPLIT* ×*INVST*)		0.009***	0.007**	0.007***	0.007**	0.007***	0.007**
ΔE(Y)/ΔX(*ASPLIT* ×(*1-INVST*))		0.003	0.004	0.002	0.004	0.001	0.004
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.5 reports the results of Eq. (5.1) using the Tobit approach with two interaction term, $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$, where $INVST_{t\,t-1}$ is a dummy that identifies firms with an investment-grade rating. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.6. Investment-grade firms and speculative-grade firms with the GLM approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times INVST_{t-1}$	+	0.035***	0.030**	0.041***	0.032*	0.043***	0.034**
		(4.20)	(2.18)	(3.17)	(1.94)	(3.34)	(1.99)
$ASPLIT_{t-1} \times (1\text{-}INVST_{t-1})$	+	0.013	0.018	0.014	0.019	0.011	0.017
		(1.49)	(1.53)	(1.14)	(1.32)	(0.83)	(1.11)
$TANG_{t-1}$	+	0.209***	0.180**	0.556***	0.539***	0.645***	0.630***
		(3.12)	(2.03)	(5.42)	(4.92)	(6.30)	(5.66)
FS_{t-1}	+	0.094***	0.129***	0.082***	0.127***	0.081***	0.129***
		(7.44)	(7.24)	(4.38)	(5.73)	(4.49)	(5.82)
MTB_{t-1}	-	-0.609***	0.038	-0.494***	0.144***	-0.495***	0.146***
		(-22.52)	(1.07)	(-13.71)	(3.06)	(-13.21)	(3.04)
$PROFIT_{t-1}$	-	-0.632***	0.162	-0.967***	0.070	-0.783**	0.290
		(-2.86)	(0.57)	(-3.09)	(0.19)	(-2.41)	(0.77)
RD_{t-1}	-	-1.644***	-1.991***	-1.769***	-1.824***	-1.838***	-1.888***
		(-4.21)	(-3.79)	(-3.23)	(-2.88)	(-3.16)	(-2.90)
EI_{t-1}	-	-0.034**	-0.026	0.006	0.019	0.023	0.035
		(-2.30)	(-1.63)	(0.27)	(0.83)	(1.02)	(1.52)
AGE_{t-1}	+	0.029**	0.051***	-0.001	0.022	0.010	0.028
		(2.32)	(2.75)	(-0.03)	(0.95)	(0.49)	(1.21)
$INDFL_{t-1}$	+	0.664***	0.844***	0.679***	0.828***	0.600***	0.749***
		(8.71)	(8.41)	(5.83)	(6.47)	(5.30)	(5.87)
Constant		-1.960***	-2.551***	-4.476***	-5.122***	-4.983***	-5.634***
		(-2.84)	(-3.08)	(-6.19)	(-5.98)	(-6.95)	(-6.61)
$\Delta Y/\Delta X(ASPLIT \times INVST)$		0.008***	0.007**	0.008***	0.008*	0.008***	0.008**
$\Delta Y/\Delta X(ASPLIT \times (1\text{-}INVST))$		0.003	0.004	0.003	0.005	0.002	0.004
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.6 reports the results of Eq. (5.1) using the GLM approach with two interaction term, $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - INVST_{t-1})$, where $INVST_{t\,t-1}$ is a dummy that identifies firms with an investment-grade rating. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Marginal effects of split ratings are presented on row title ΔY/ΔX. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.7. Crisis and non-crisis period with the Tobit approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times CRISIS_{t-1}$	+	0.010***	0.005	0.012***	0.007	0.011***	0.008
		(3.23)	(1.47)	(2.87)	(1.43)	(2.63)	(1.49)
$ASPLIT_{t-1} \times (1\text{-}CRISIS_{-1})$	+	0.005***	0.005**	0.004**	0.006**	0.003*	0.005**
		(3.05)	(2.39)	(2.12)	(2.14)	(1.84)	(1.96)
$TANG_{t-1}$	+	0.050***	0.040**	0.116***	0.128***	0.131***	0.148***
		(3.05)	(2.01)	(5.25)	(4.96)	(6.12)	(5.71)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.030***	0.018***	0.030***
		(7.77)	(7.21)	(4.81)	(5.70)	(4.96)	(5.80)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.034***	-0.059***	0.033***
		(-18.89)	(0.98)	(-10.59)	(3.06)	(-9.99)	(2.99)
$PROFIT_{t-1}$	-	-0.168***	0.032	-0.195***	0.012	-0.157**	0.061
		(-3.26)	(0.48)	(-3.08)	(0.14)	(-2.49)	(0.69)
RD_{t-1}	-	-0.297***	-0.476***	-0.223**	-0.419***	-0.219**	-0.422***
		(-3.42)	(-3.75)	(-2.36)	(-2.85)	(-2.29)	(-2.88)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.000	0.008
		(-2.39)	(-1.55)	(-0.64)	(0.82)	(-0.09)	(1.50)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.52)	(2.71)	(0.27)	(0.92)	(0.80)	(1.18)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.177***
		(9.28)	(8.47)	(6.24)	(6.53)	(5.77)	(5.91)
Constant		0.006	-0.085	-0.225	-0.439**	-0.252	-0.477**
		(0.04)	(-0.42)	(-1.39)	(-2.07)	(-1.59)	(-2.25)
ΔY*/ΔX(*ASPLIT* ×*CRISIS*)		0.010***	0.005	0.011***	0.007	0.010***	0.008
ΔY*/ΔX(*ASPLIT* ×(*1-CRISIS*))		0.005***	0.005**	0.004**	0.006**	0.003*	0.005**
ΔE(Y)/ΔX(*ASPLIT* ×*CRISIS*)		0.010***	0.005	0.010***	0.007	0.009***	0.007
ΔE(Y)/ΔX(*ASPLIT* ×(*1-CRISIS*))		0.005***	0.005**	0.003**	0.005**	0.003*	0.005**
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.7 reports the results of Eq. (5.1) using the Tobit approach with two interaction term, $ASPLIT_{t-1} \times CRISIS_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$, where $CRISIS_{t-1}$ is a dummy that identifies the crisis period (2007 – 2009). The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.8. Crisis and non-crisis period with the GLM approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1} \times CRISIS_{t-1}$	+	0.045***	0.025	0.052***	0.030	0.050**	0.033
		(3.32)	(1.55)	(2.69)	(1.40)	(2.49)	(1.51)
$ASPLIT_{t-1} \times (1\text{-}CRISIS_{t-1})$	+	0.019***	0.023**	0.019**	0.024**	0.017*	0.023*
		(2.80)	(2.46)	(2.01)	(2.08)	(1.78)	(1.91)
$TANG_{t-1}$	+	0.210***	0.180**	0.557***	0.539***	0.646***	0.630***
		(3.13)	(2.03)	(5.44)	(4.91)	(6.33)	(5.66)
FS_{t-1}	+	0.093***	0.129***	0.081***	0.127***	0.080***	0.129***
		(7.37)	(7.22)	(4.33)	(5.70)	(4.44)	(5.79)
MTB_{t-1}	-	-0.610***	0.038	-0.495***	0.144***	-0.497***	0.146***
		(-22.49)	(1.07)	(-13.70)	(3.07)	(-13.20)	(3.04)
$PROFIT_{t-1}$	-	-0.642***	0.155	-0.978***	0.063	-0.796**	0.281
		(-2.90)	(0.55)	(-3.11)	(0.17)	(-2.44)	(0.74)
RD_{t-1}	-	-1.628***	-1.979***	-1.750***	-1.811***	-1.816***	-1.870***
		(-4.18)	(-3.78)	(-3.20)	(-2.87)	(-3.12)	(-2.88)
EI_{t-1}	-	-0.033**	-0.026	0.007	0.020	0.024	0.036
		(-2.26)	(-1.60)	(0.31)	(0.85)	(1.08)	(1.55)
AGE_{t-1}	+	0.029**	0.051***	-0.001	0.021	0.009	0.028
		(2.29)	(2.74)	(-0.05)	(0.94)	(0.46)	(1.20)
$INDFL_{t-1}$	+	0.665***	0.844***	0.680***	0.829***	0.602***	0.750***
		(8.72)	(8.43)	(5.84)	(6.49)	(5.32)	(5.89)
Constant		-1.969***	-2.561***	-4.485***	-5.132***	-4.995***	-5.645***
		(-2.85)	(-3.09)	(-6.20)	(-5.99)	(-6.97)	(-6.62)
$\Delta Y/\Delta X(ASPLIT \times CRISIS)$		0.010***	0.006	0.010***	0.007	0.009**	0.008
$\Delta Y/\Delta X(ASPLIT \times (1\text{-}CRISIS))$		0.004***	0.005**	0.004**	0.006**	0.003*	0.005*
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.8 reports the results of Eq. (5.1) using the GLM approach with two interaction term, $ASPLIT_{t-1} \times CRISIS_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$. The key variables of interest are $ASPLIT_{t-1} \times INVST_{t-1}$ and $ASPLIT_{t-1} \times (1 - CRISIS_{t-1})$, where $CRISIS_{t-1}$ is a dummy that identifies the crisis period (2007 – 2009). The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Marginal effects of split ratings are presented on row title ΔY/ΔX. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.9. Tobit regression using the PSM sample (NN matching without replacement).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.008***	0.008***	0.011***	0.008***	0.011***
		(4.00)	(2.66)	(3.67)	(3.14)	(3.76)	(3.29)
$TANG_{t-1}$	-0.035	0.075***	0.067***	0.142***	0.155***	0.152***	0.168***
	(-0.33)	(3.62)	(2.71)	(5.70)	(4.91)	(6.24)	(5.36)
FS_{t-1}	0.010	0.025***	0.032***	0.020***	0.034***	0.017***	0.032***
	(0.27)	(6.30)	(6.11)	(3.95)	(4.89)	(3.85)	(4.84)
MTB_{t-1}	0.010	-0.087***	0.033***	-0.039***	0.068***	-0.038***	0.064***
	(0.27)	(-12.65)	(3.29)	(-6.02)	(5.20)	(-6.04)	(4.99)
$PROFIT_{t-1}$		-0.148**	0.103	-0.199**	0.081	-0.157**	0.140
		(-2.18)	(1.17)	(-2.57)	(0.70)	(-2.06)	(1.22)
RD_{t-1}		-0.200*	-0.561***	-0.190*	-0.655***	-0.192*	-0.666***
		(-1.92)	(-3.36)	(-1.84)	(-3.34)	(-1.86)	(-3.49)
EI_{t-1}		-0.008*	-0.007	-0.001	0.003	-0.001	0.005
		(-1.85)	(-1.30)	(-0.30)	(0.48)	(-0.15)	(0.81)
AGE_{t-1}		0.009**	0.018***	0.004	0.013*	0.005	0.013**
		(2.45)	(3.14)	(0.91)	(1.93)	(1.18)	(2.04)
$INDFL_{t-1}$		0.200***	0.224***	0.158***	0.221***	0.132***	0.196***
		(9.03)	(8.15)	(5.78)	(6.30)	(5.00)	(5.69)
$IDIO_{t-1}$	0.020***						
	(3.74)						
$TAXES_{-1}$	-4.673***						
	(-4.98)						
$CASH_{-1}$	-0.247						
	(-1.04)						
Constant	-0.745	0.297***	0.384***	0.120	0.203	0.131	0.216*
	(-1.14)	(3.68)	(4.43)	(1.13)	(1.61)	(1.28)	(1.75)
ΔY*/ΔX		0.007***	0.008***	0.007***	0.011***	0.007***	0.011***
ΔE(Y)/ΔX		0.007***	0.007***	0.007***	0.010***	0.006***	0.010***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,345	2,480	2,480	2,480	2,480	2,480	2,480
Pseudo R-squared	0.108						
No. of firms		655	655	655	655	655	655

Note: Table 5.B.9 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the Tobit approach with a matched sample. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.10. GLM regression using the PSM sample (NN matching without replacement).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.032***	0.034***	0.042***	0.046***	0.044***	0.049***
		(3.86)	(2.71)	(3.60)	(3.08)	(3.81)	(3.28)
$TANG_{t-1}$	-0.035	0.323***	0.302***	0.730***	0.666***	0.807***	0.731***
	(-0.33)	(3.79)	(2.80)	(5.85)	(4.84)	(6.32)	(5.27)
FS_{t-1}	0.010	0.100***	0.140***	0.097***	0.151***	0.087***	0.145***
	(0.27)	(5.95)	(6.12)	(3.71)	(4.90)	(3.56)	(4.87)
MTB_{t-1}	0.010	-0.503***	0.144***	-0.361***	0.297***	-0.384***	0.288***
	(0.27)	(-14.34)	(3.29)	(-8.36)	(5.20)	(-8.71)	(5.06)
$PROFIT_{t-1}$		-0.562*	0.438	-1.062**	0.324	-0.839*	0.602
		(-1.88)	(1.15)	(-2.49)	(0.63)	(-1.93)	(1.16)
RD_{t-1}		-1.247**	-2.323***	-1.691**	-2.876***	-1.806**	-2.984***
		(-2.44)	(-3.36)	(-2.47)	(-3.26)	(-2.51)	(-3.37)
EI_{t-1}		-0.035*	-0.030	0.007	0.013	0.016	0.023
		(-1.73)	(-1.28)	(0.24)	(0.46)	(0.51)	(0.77)
AGE_{t-1}		0.038**	0.077***	0.021	0.056**	0.028	0.060**
		(2.40)	(3.17)	(0.88)	(1.99)	(1.17)	(2.10)
$INDFL_{t-1}$		0.780***	0.974***	0.729***	0.931***	0.616***	0.838***
		(8.51)	(8.09)	(5.24)	(6.21)	(4.34)	(5.60)
$IDIO_{t-1}$	0.020***						
	(3.74)						
$TAXES_{-1}$	-4.673***						
	(-4.98)						
$CASH_{-1}$	-0.247						
	(-1.04)						
Constant	-0.745	-0.553	-0.251	-1.337***	-1.068	-1.277***	-1.064
	(-1.14)	(-1.49)	(-0.38)	(-2.78)	(-1.52)	(-2.74)	(-1.54)
ΔY/ΔX		0.007***	0.008***	0.007***	0.010***	0.007***	0.011***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,345	2,480	2,480	2,480	2,480	2,480	2,480
Pseudo R-squared	0.108						
No. of firms		655	655	655	655	655	655

Note: Table 5.B.10 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the GLM approach with a matched sample. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3, BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.11. Matching quality tests for NN matching without replacement and the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
$IDIO_{t-1}$	U	9.739	7.905	33.2		9.79	0.000
	M	8.826	8.612	3.9	88.4	1.06	0.291
$CASH_{-1}$	U	0.082	0.092	-11		-3.74	0.000
	M	0.082	0.086	-4.9	55.8	-1.2	0.230
FS_{t-1}	U	8.384	8.876	-36		-11.75	0.000
	M	8.496	8.491	0.3	99	0.09	0.931
MTB_{t-1}	U	1.197	1.360	-23.3		-7.86	0.000
	M	1.229	1.248	-2.8	88.1	-0.71	0.476
$TANG_{t-1}$	U	0.368	0.355	5.2		1.71	0.088
	M	0.368	0.359	3.6	31.4	0.87	0.387

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
MDR1	Unmatched	0.461	0.394	0.067	0.006	11.86***
	ATT	0.449	0.422	0.027	0.009	2.96***
BDR1	Unmatched	0.631	0.593	0.039	0.005	8.25***
	ATT	0.629	0.600	0.029	0.008	3.73***
MDR2	Unmatched	0.321	0.248	0.073	0.006	12.23***
	ATT	0.307	0.276	0.032	0.010	3.24***
BDR2	Unmatched	0.474	0.411	0.063	0.006	9.87***
	ATT	0.469	0.429	0.040	0.011	3.81***
MDR3	Unmatched	0.301	0.229	0.072	0.006	12.15***
	ATT	0.288	0.256	0.032	0.010	3.33***
BDR3	Unmatched	0.449	0.384	0.064	0.007	9.88***
	ATT	0.442	0.401	0.041	0.011	3.77***

Panel C. Pseudo R-square test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.102	676.47	0.00	5.8	3.9	80.6*	0.890	80
Matched	0.027	87.99	0.91	3	2.6	39.1*	1.080	20

Note: Table 5.B.11 shows various matching quality tests for NN matching with replacement and caliper of 0.01. Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the $SPLIT\_DUM_{t-1}$ variable, which equals one if firms are split rated at time $t-1$ and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), idiosyncratic risk (*IDIO*), asset tangibility (*TANG*) and book value of cash over total asset (*CASH*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R-square and the joint-significance tests.

Table 5.B.12. OLS regression using the PSM sample (NN matching with replacement).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.009***	0.008***	0.012***	0.007***	0.011***
		(4.15)	(3.64)	(3.35)	(3.51)	(2.89)	(3.30)
$TANG_{t-1}$	-0.095	0.076***	0.074***	0.128***	0.149***	0.139***	0.162***
	(-0.92)	(3.54)	(3.17)	(4.52)	(5.17)	(4.89)	(5.75)
FS_{t-1}	0.010	0.019***	0.027***	0.014***	0.025***	0.012***	0.024***
	(0.48)	(5.18)	(5.64)	(2.88)	(3.75)	(2.70)	(3.72)
MTB_{t-1}	-0.054	-0.108***	0.011	-0.059***	0.040***	-0.057***	0.038***
	(-1.62)	(-15.05)	(1.08)	(-8.35)	(3.10)	(-8.14)	(3.04)
$PROFIT_{t-1}$		-0.124*	0.109	-0.200**	0.042	-0.154*	0.113
		(-1.77)	(1.14)	(-2.44)	(0.33)	(-1.87)	(0.88)
RD_{t-1}		-0.321***	-0.518***	-0.215**	-0.406**	-0.241**	-0.472***
		(-3.16)	(-3.84)	(-2.00)	(-2.26)	(-2.19)	(-2.99)
EI_{t-1}		0.003	0.010	0.005	0.019**	0.005	0.020**
		(0.65)	(1.51)	(0.99)	(2.20)	(1.02)	(2.38)
AGE_{t-1}		0.008**	0.017***	0.003	0.012**	0.003	0.012**
		(2.32)	(3.35)	(0.63)	(2.09)	(0.82)	(2.01)
$INDFL_{t-1}$		0.218***	0.207***	0.195***	0.219***	0.166***	0.191***
		(9.21)	(7.61)	(6.33)	(6.06)	(5.46)	(5.34)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	0.299***	0.287***	0.189***	0.127	0.165***	0.093
	(-2.18)	(5.88)	(4.99)	(2.99)	(1.63)	(2.73)	(1.18)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	10,396	10,396	10,396	10,396	10,396	10,396
Pseudo R-squared	0.102						
Adjusted R-squared		0.637	0.303	0.576	0.358	0.569	0.361
No. of firms		865	865	865	865	865	865

Note: Table 5.B.12 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the OLS approach with a matched sample. The matching method is NN matching with replacement and with the caliper of 0.01. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.13. Tobit regression using the PSM sample (NN matching with replacement).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.009***	0.008***	0.012***	0.007***	0.011***
		(4.17)	(3.66)	(3.36)	(3.49)	(2.89)	(3.26)
$TANG_{t-1}$	-0.095	0.076***	0.074***	0.129***	0.151***	0.140***	0.164***
	(-0.92)	(3.56)	(3.18)	(4.58)	(5.22)	(4.94)	(5.78)
FS_{t-1}	0.010	0.019***	0.027***	0.013***	0.025***	0.012**	0.024***
	(0.48)	(5.21)	(5.68)	(2.78)	(3.66)	(2.49)	(3.53)
MTB_{t-1}	-0.054	-0.108***	0.011	-0.060***	0.040***	-0.058***	0.038***
	(-1.62)	(-15.14)	(1.09)	(-8.17)	(3.02)	(-8.03)	(2.94)
$PROFIT_{t-1}$		-0.124*	0.109	-0.188**	0.054	-0.137	0.132
		(-1.78)	(1.15)	(-2.17)	(0.40)	(-1.53)	(0.96)
RD_{t-1}		-0.321***	-0.518***	-0.232**	-0.426**	-0.276**	-0.512***
		(-3.18)	(-3.86)	(-2.00)	(-2.20)	(-2.32)	(-3.05)
EI_{t-1}		0.003	0.010	0.005	0.019**	0.005	0.019**
		(0.65)	(1.52)	(0.98)	(2.20)	(0.92)	(2.33)
AGE_{t-1}		0.008**	0.017***	0.003	0.012**	0.004	0.012**
		(2.33)	(3.37)	(0.67)	(2.12)	(0.87)	(2.05)
$INDFL_{t-1}$		0.218***	0.207***	0.197***	0.221***	0.170***	0.195***
		(9.26)	(7.66)	(6.32)	(6.05)	(5.44)	(5.30)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	0.299***	0.287***	0.184***	0.122	0.161***	0.086
	(-2.18)	(5.91)	(5.02)	(2.90)	(1.55)	(2.63)	(1.07)
ΔY*/ΔX		0.008***	0.009***	0.008***	0.011***	0.007***	0.011***
ΔE(Y)/ΔX		0.008***	0.009***	0.007***	0.011***	0.006***	0.010***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	10,396	10,396	10,396	10,396	10,396	10,396
Pseudo R-squared	0.102						
No. of firms		865	865	865	865	865	865

Note: Table 5.B.13 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the Tobit approach with a matched sample. The matching method is NN matching with replacement and with the caliper of 0.01. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2,* and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.14. GLM regression using the PSM sample (NN matching with replacement).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.034***	0.040***	0.041***	0.049***	0.037***	0.047***
		(3.92)	(3.74)	(3.34)	(3.43)	(2.95)	(3.21)
$TANG_{t-1}$	-0.095	0.310***	0.330***	0.608***	0.633***	0.679***	0.691***
	(-0.92)	(3.42)	(3.24)	(4.73)	(5.12)	(5.20)	(5.67)
FS_{t-1}	0.010	0.074***	0.120***	0.061***	0.107***	0.056**	0.106***
	(0.48)	(4.86)	(5.74)	(2.70)	(3.74)	(2.50)	(3.71)
MTB_{t-1}	-0.054	-0.595***	0.051	-0.480***	0.171***	-0.497***	0.164***
	(-1.62)	(-16.96)	(1.15)	(-10.58)	(3.00)	(-10.58)	(2.92)
$PROFIT_{t-1}$		-0.406	0.464	-0.848**	0.232	-0.605	0.567
		(-1.32)	(1.14)	(-1.99)	(0.41)	(-1.37)	(0.98)
RD_{t-1}		-1.752***	-2.132***	-1.607**	-1.819**	-1.875***	-2.182***
		(-3.80)	(-3.84)	(-2.36)	(-2.15)	(-2.76)	(-2.83)
EI_{t-1}		0.025	0.042	0.074**	0.089**	0.085**	0.096**
		(1.05)	(1.48)	(2.17)	(2.21)	(2.47)	(2.44)
AGE_{t-1}		0.035**	0.074***	0.016	0.052**	0.021	0.052**
		(2.32)	(3.36)	(0.76)	(2.12)	(1.01)	(2.06)
$INDFL_{t-1}$		0.854***	0.908***	0.867***	0.922***	0.746***	0.812***
		(8.64)	(7.60)	(5.92)	(6.00)	(5.03)	(5.30)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	-0.632***	-0.958***	-1.141***	-1.586***	-1.259***	-1.757***
	(-2.18)	(-2.96)	(-3.81)	(-3.94)	(-4.73)	(-4.38)	(-5.10)
ΔY/ΔX		0.008***	0.009***	0.008***	0.011***	0.007***	0.011***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	10,396	10,396	10,396	10,396	10,396	10,396
Pseudo R-squared	0.102						
No. of firms		865	865	865	865	865	865

Note: Table 5.B.14 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the GLM approach with a matched sample. The matching method is NN matching with replacement and with the caliper of 0.01. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.15. Matching quality tests for radius matching and the caliper of 0.01.

Panel A. Standardised bias test

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
IDIO$_{t-1}$	U	9.739	7.905	33.2		9.79	0.000
	M	8.826	8.620	3.7	88.8	1.02	0.309
CASH$_{-1}$	U	0.082	0.092	-11		-3.74	0.000
	M	0.082	0.087	-5.2	52.7	-1.28	0.201
FS$_{t-1}$	U	8.384	8.876	-36		-11.75	0.000
	M	8.496	8.485	0.8	97.8	0.2	0.845
MTB$_{t-1}$	U	1.197	1.360	-23.3		-7.86	0.000
	M	1.229	1.245	-2.4	89.7	-0.62	0.537
TANG$_{t-1}$	U	0.368	0.355	5.2		1.71	0.088
	M	0.368	0.360	3.2	39.3	0.76	0.446

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
MDR1	Unmatched	0.461	0.394	0.067	0.006	11.86***
	ATT	0.449	0.420	0.029	0.009	3.22***
BDR1	Unmatched	0.631	0.593	0.039	0.005	8.25***
	ATT	0.629	0.597	0.032	0.008	4.06***
MDR2	Unmatched	0.321	0.248	0.073	0.006	12.23***
	ATT	0.307	0.274	0.034	0.010	3.54***
BDR2	Unmatched	0.474	0.411	0.063	0.006	9.87***
	ATT	0.469	0.426	0.043	0.010	4.07***
MDR3	Unmatched	0.301	0.229	0.072	0.006	12.15***
	ATT	0.288	0.253	0.034	0.009	3.63***
BDR3	Unmatched	0.449	0.384	0.064	0.007	9.88***
	ATT	0.442	0.399	0.043	0.011	4.01***

Panel C. Pseudo R-square test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.102	676.47	0.00	5.8	3.9	80.6*	0.890	80
Matched	0.027	89.16	0.89	3	2.5	39.4*	1.050	40

Note: Table 5.B.15 shows various matching quality tests for radius matching and caliper of 0.01. Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the *SPLIT_DUM*$_{t-1}$ variable, which equals one if firms are split rated at time $t-1$ and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), idiosyncratic risk (*IDIO*), asset tangibility (*TANG*) and book value of cash over total asset (*CASH*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R-square and the joint-significance tests.

Table 5.B.16. OLS regression using the PSM sample (radius matching).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.008***	0.008***	0.010***	0.007***	0.009***
		(3.96)	(3.08)	(3.33)	(3.13)	(2.87)	(2.83)
$TANG_{t-1}$	-0.095	0.072***	0.073***	0.123***	0.146***	0.137***	0.162***
	(-0.92)	(3.25)	(2.72)	(4.44)	(4.61)	(5.04)	(5.30)
FS_{t-1}	0.010	0.023***	0.029***	0.018***	0.028***	0.017***	0.028***
	(0.48)	(6.30)	(6.09)	(3.91)	(4.45)	(3.80)	(4.45)
MTB_{t-1}	-0.054	-0.109***	0.010	-0.059***	0.039***	-0.057***	0.037***
	(-1.62)	(-15.53)	(1.03)	(-8.53)	(3.16)	(-8.28)	(3.04)
$PROFIT_{t-1}$		-0.107	0.118	-0.171**	0.059	-0.122	0.126
		(-1.56)	(1.31)	(-2.16)	(0.51)	(-1.55)	(1.09)
RD_{t-1}		-0.337***	-0.524***	-0.267**	-0.481***	-0.274**	-0.505***
		(-2.98)	(-3.72)	(-2.26)	(-2.59)	(-2.34)	(-2.93)
EI_{t-1}		0.000	0.003	0.002	0.011	0.003	0.013*
		(0.02)	(0.48)	(0.37)	(1.44)	(0.67)	(1.85)
AGE_{t-1}		0.009**	0.017***	0.003	0.012*	0.005	0.013**
		(2.25)	(3.10)	(0.71)	(1.94)	(1.16)	(2.16)
$INDFL_{t-1}$		0.197***	0.193***	0.168***	0.193***	0.136***	0.160***
		(8.30)	(7.13)	(5.49)	(5.55)	(4.56)	(4.68)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	0.293***	0.295***	0.182***	0.135*	0.154**	0.096
	(-2.18)	(5.68)	(4.91)	(2.89)	(1.71)	(2.58)	(1.18)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	6,511	6,511	6,511	6,511	6,511	6,511
Pseudo R-squared	0.102						
Adjusted R-squared		0.611	0.275	0.547	0.336	0.541	0.342
No. of firms		869	869	869	869	869	869

Note: Table 5.B.16 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the OLS approach with a matched sample. The matching method is radius matching and with the caliper of 0.01. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.17. Tobit regression using the PSM sample (radius matching).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.008***	0.008***	0.011***	0.007***	0.010***
		(4.00)	(3.11)	(3.38)	(3.17)	(2.92)	(2.87)
$TANG_{t-1}$	-0.095	0.072***	0.073***	0.124***	0.148***	0.138***	0.164***
	(-0.92)	(3.28)	(2.75)	(4.52)	(4.68)	(5.11)	(5.37)
FS_{t-1}	0.010	0.023***	0.029***	0.018***	0.028***	0.017***	0.028***
	(0.48)	(6.36)	(6.15)	(3.88)	(4.44)	(3.70)	(4.39)
MTB_{t-1}	-0.054	-0.109***	0.010	-0.060***	0.039***	-0.058***	0.037***
	(-1.62)	(-15.68)	(1.04)	(-8.37)	(3.12)	(-8.17)	(2.94)
$PROFIT_{t-1}$		-0.107	0.118	-0.165**	0.064	-0.113	0.136
		(-1.57)	(1.33)	(-2.03)	(0.54)	(-1.37)	(1.13)
RD_{t-1}		-0.337***	-0.524***	-0.288**	-0.504**	-0.305**	-0.541***
		(-3.01)	(-3.75)	(-2.25)	(-2.54)	(-2.42)	(-2.95)
EI_{t-1}		0.000	0.003	0.002	0.010	0.003	0.013*
		(0.02)	(0.48)	(0.33)	(1.38)	(0.62)	(1.79)
AGE_{t-1}		0.009**	0.017***	0.003	0.012*	0.005	0.013**
		(2.27)	(3.12)	(0.73)	(1.96)	(1.19)	(2.19)
$INDFL_{t-1}$		0.197***	0.193***	0.169***	0.195***	0.137***	0.161***
		(8.38)	(7.20)	(5.52)	(5.58)	(4.58)	(4.69)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	0.293***	0.295***	0.177***	0.129	0.149**	0.089
	(-2.18)	(5.74)	(4.96)	(2.79)	(1.62)	(2.48)	(1.09)
ΔY*/ΔX		0.008***	0.008***	0.007***	0.010***	0.006***	0.009***
ΔE(Y)/ΔX		0.008***	0.008***	0.007***	0.010***	0.006***	0.008***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	6,511	6,511	6,511	6,511	6,511	6,511
Pseudo R-squared	0.102						
No. of firms		865	865	865	865	865	865

Note: Table 5.B.17 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the Tobit approach with a matched sample. The matching method is radius matching and with the caliper of 0.01. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.18. GLM regression using the PSM sample (radius matching).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.033***	0.036***	0.040***	0.044***	0.036***	0.040***
		(3.87)	(3.19)	(3.37)	(3.10)	(2.97)	(2.80)
$TANG_{t-1}$	-0.095	0.296***	0.326***	0.590***	0.620***	0.672***	0.694***
	(-0.92)	(3.18)	(2.80)	(4.60)	(4.60)	(5.25)	(5.28)
FS_{t-1}	0.010	0.090***	0.129***	0.082***	0.122***	0.077***	0.121***
	(0.48)	(5.95)	(6.19)	(3.68)	(4.46)	(3.53)	(4.46)
MTB_{t-1}	-0.054	-0.601***	0.045	-0.478***	0.167***	-0.492***	0.161***
	(-1.62)	(-17.84)	(1.10)	(-11.02)	(3.11)	(-10.92)	(2.98)
$PROFIT_{t-1}$		-0.345	0.513	-0.767*	0.273	-0.506	0.581
		(-1.16)	(1.34)	(-1.90)	(0.55)	(-1.22)	(1.15)
RD_{t-1}		-1.819***	-2.153***	-1.960***	-2.138**	-2.091***	-2.302***
		(-3.48)	(-3.73)	(-2.66)	(-2.51)	(-2.81)	(-2.81)
EI_{t-1}		0.006	0.010	0.046	0.049	0.062**	0.063*
		(0.30)	(0.43)	(1.50)	(1.49)	(2.02)	(1.92)
AGE_{t-1}		0.036**	0.074***	0.016	0.051**	0.026	0.058**
		(2.21)	(3.17)	(0.71)	(1.99)	(1.19)	(2.22)
$INDFL_{t-1}$		0.762***	0.846***	0.739***	0.814***	0.601***	0.682***
		(7.82)	(7.19)	(5.12)	(5.54)	(4.15)	(4.68)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	-0.653***	-0.929***	-1.169***	-1.549***	-1.313***	-1.741***
	(-2.18)	(-3.05)	(-3.56)	(-4.09)	(-4.59)	(-4.69)	(-5.00)
ΔY/ΔX		0.008***	0.008***	0.008***	0.010***	0.007***	0.009***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	6,511	6,511	6,511	6,511	6,511	6,511
Pseudo R-squared	0.102						
No. of firms		865	865	865	865	865	865

Note: Table 5.B.18 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the GLM approach with a matched sample. The matching method is radius matching and with the caliper of 0.01. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.19. Matching quality tests for kernel matching with the bandwidth of 0.06.

Panel A. Standardised bias test

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|t|
$IDIO_{t-1}$	U	9.739	7.905	33.2		9.79	0
	M	8.826	8.612	3.9	88.4	1.06	0.291
$CASH_{-1}$	U	0.082	0.092	-11		-3.74	0
	M	0.082	0.087	-5	54.9	-1.23	0.22
FS_{t-1}	U	8.384	8.876	-36		-11.75	0
	M	8.496	8.484	0.8	97.7	0.21	0.832
MTB_{t-1}	U	1.197	1.360	-23.3		-7.86	0
	M	1.229	1.246	-2.4	89.5	-0.63	0.529
$TANG_{t-1}$	U	0.368	0.355	5.2		1.71	0.088
	M	0.368	0.360	3.1	40.3	0.75	0.453

Panel B. Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
MDR1	Unmatched	0.461	0.394	0.067	0.006	11.86***
	ATT	0.449	0.420	0.029	0.009	3.14***
BDR1	Unmatched	0.631	0.593	0.039	0.005	8.25***
	ATT	0.629	0.599	0.030	0.008	3.89***
MDR2	Unmatched	0.321	0.248	0.073	0.006	12.23***
	ATT	0.307	0.274	0.033	0.010	3.46***
BDR2	Unmatched	0.474	0.411	0.063	0.006	9.87***
	ATT	0.469	0.428	0.041	0.010	3.93***
MDR3	Unmatched	0.301	0.229	0.072	0.006	12.15***
	ATT	0.288	0.254	0.033	0.009	3.54***
BDR3	Unmatched	0.449	0.384	0.064	0.007	9.88***
	ATT	0.442	0.401	0.041	0.011	3.86***

Panel C. Pseudo R-square test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.102	676.47	0	5.8	3.9	80.6*	0.89	80
Matched	0.028	89.82	0.884	3	2.4	39.5*	1.05	40

Note: Table 5.B.19 shows various matching quality tests for kernel matching using Epanechnikov kernel function with the bandwidth of 0.06. Panel A reports the results of the standardised bias test on propensity score specification. The treated criteria is split rating specified by the $SPLIT\_DUM_{t-1}$ variable, which equals one if firms are split rated at time $t-1$ and zero otherwise. The interested covariates are firm size (*FS*), market-to-book ratio (*MTB*), idiosyncratic risk (*IDIO*), asset tangibility (*TANG*) and book value of cash over total asset (*CASH*). Panel B reports the average treatment effect on treated (ATT) results. Panel C reports the results of the Pseudo R-square and the joint-significance tests.

Table 5.B.20. OLS regression using the PSM sample (kernel matching).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.008***	0.008***	0.010***	0.007***	0.009***
		(4.08)	(3.07)	(3.42)	(3.08)	(3.01)	(2.84)
$TANG_{t-1}$	-0.095	0.068***	0.057**	0.121***	0.131***	0.138***	0.149***
	(-0.92)	(3.28)	(2.24)	(4.57)	(4.13)	(5.33)	(4.85)
FS_{t-1}	0.010	0.023***	0.030***	0.019***	0.030***	0.018***	0.030***
	(0.48)	(6.67)	(6.27)	(4.21)	(4.73)	(4.07)	(4.75)
MTB_{t-1}	-0.054	-0.108***	0.012	-0.058***	0.042***	-0.055***	0.041***
	(-1.62)	(-15.34)	(1.27)	(-8.33)	(3.43)	(-8.08)	(3.33)
$PROFIT_{t-1}$		-0.133**	0.094	-0.196***	0.037	-0.147*	0.105
		(-2.03)	(1.08)	(-2.58)	(0.33)	(-1.94)	(0.93)
RD_{t-1}		-0.380***	-0.584***	-0.319***	-0.573***	-0.327***	-0.605***
		(-3.26)	(-4.06)	(-2.67)	(-3.13)	(-2.74)	(-3.56)
EI_{t-1}		0.000	0.003	0.002	0.012	0.004	0.015**
		(0.09)	(0.53)	(0.49)	(1.57)	(0.78)	(1.98)
AGE_{t-1}		0.008**	0.016***	0.003	0.011*	0.006	0.013**
		(2.23)	(3.06)	(0.74)	(1.90)	(1.27)	(2.17)
$INDFL_{t-1}$		0.187***	0.190***	0.159***	0.191***	0.125***	0.156***
		(8.37)	(7.36)	(5.38)	(5.59)	(4.39)	(4.66)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	0.313***	0.309***	0.198***	0.144*	0.166***	0.099
	(-2.18)	(6.06)	(5.20)	(3.11)	(1.82)	(2.75)	(1.21)
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	6,530	6,530	6,530	6,530	6,530	6,530
Pseudo R-squared	0.102						
Adjusted R-squared		0.609	0.271	0.540	0.331	0.533	0.337
No. of firms		869	869	869	869	869	869

Note: Table 5.B.20 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the OLS approach with a matched sample. The matching method is kernel matching with the bandwidth of 0.06. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time *t – 1* and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time *t – 1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.21. Tobit regression using the PSM sample (kernel matching).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.008***	0.008***	0.008***	0.010***	0.007***	0.010***
		(4.11)	(3.10)	(3.47)	(3.12)	(3.06)	(2.89)
$TANG_{t-1}$	-0.095	0.068***	0.057**	0.123***	0.132***	0.139***	0.151***
	(-0.92)	(3.31)	(2.26)	(4.64)	(4.19)	(5.39)	(4.90)
FS_{t-1}	0.010	0.023***	0.030***	0.019***	0.030***	0.017***	0.029***
	(0.48)	(6.73)	(6.33)	(4.18)	(4.73)	(3.98)	(4.69)
MTB_{t-1}	-0.054	-0.108***	0.012	-0.058***	0.042***	-0.056***	0.040***
	(-1.62)	(-15.48)	(1.28)	(-8.18)	(3.40)	(-7.96)	(3.26)
$PROFIT_{t-1}$		-0.133**	0.094	-0.192**	0.041	-0.139*	0.113
		(-2.05)	(1.09)	(-2.46)	(0.36)	(-1.76)	(0.97)
RD_{t-1}		-0.380***	-0.584***	-0.344***	-0.601***	-0.364***	-0.648***
		(-3.29)	(-4.10)	(-2.63)	(-3.04)	(-2.78)	(-3.54)
EI_{t-1}		0.000	0.003	0.002	0.012	0.004	0.014*
		(0.09)	(0.53)	(0.46)	(1.52)	(0.74)	(1.93)
AGE_{t-1}		0.008**	0.016***	0.004	0.011*	0.006	0.013**
		(2.25)	(3.09)	(0.76)	(1.92)	(1.31)	(2.20)
$INDFL_{t-1}$		0.187***	0.190***	0.159***	0.192***	0.126***	0.157***
		(8.44)	(7.43)	(5.41)	(5.62)	(4.40)	(4.66)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	0.313***	0.309***	0.193***	0.139*	0.162***	0.092
	(-2.18)	(6.12)	(5.25)	(3.01)	(1.72)	(2.64)	(1.11)
ΔY*/ΔX		0.008***	0.008***	0.007***	0.010***	0.007***	0.009***
ΔE(Y)/ΔX		0.008***	0.008***	0.007***	0.009***	0.006***	0.008***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	6,530	6,530	6,530	6,530	6,530	6,530
Pseudo R-squared	0.102						
No. of firms		869	869	869	869	869	869

Note: Table 5.B.21 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the Tobit approach with a matched sample. The matching method is kernel matching with the bandwidth of 0.06. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics (z-statistics for Column (I)). Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.22. GLM regression using the PSM sample (kernel matching).

Variables	Probit (I)	*MDR1* (II)	*BDR1* (III)	*MDR2* (IV)	*BDR2* (V)	*MDR3* (VI)	*BDR3* (VII)
$ASPLIT_{t-1}$		0.033***	0.035***	0.040***	0.042***	0.036***	0.039***
		(3.99)	(3.18)	(3.45)	(3.05)	(3.09)	(2.81)
$TANG_{t-1}$	-0.095	0.275***	0.259**	0.574***	0.552***	0.667***	0.635***
	(-0.92)	(3.21)	(2.31)	(4.69)	(4.12)	(5.48)	(4.83)
FS_{t-1}	0.010	0.092***	0.134***	0.085***	0.129***	0.080***	0.128***
	(0.48)	(6.33)	(6.37)	(3.99)	(4.75)	(3.82)	(4.76)
MTB_{t-1}	-0.054	-0.595***	0.055	-0.471***	0.181***	-0.484***	0.175***
	(-1.62)	(-17.67)	(1.34)	(-10.78)	(3.37)	(-10.69)	(3.26)
$PROFIT_{t-1}$		-0.455	0.419	-0.896**	0.175	-0.635	0.482
		(-1.61)	(1.13)	(-2.33)	(0.36)	(-1.61)	(0.98)
RD_{t-1}		-2.055***	-2.406***	-2.373***	-2.565***	-2.556***	-2.784***
		(-3.80)	(-4.08)	(-3.19)	(-3.02)	(-3.39)	(-3.41)
EI_{t-1}		0.008	0.011	0.050	0.055	0.067**	0.069**
		(0.35)	(0.48)	(1.60)	(1.61)	(2.14)	(2.05)
AGE_{t-1}		0.035**	0.071***	0.016	0.049*	0.028	0.057**
		(2.21)	(3.14)	(0.72)	(1.94)	(1.29)	(2.22)
$INDFL_{t-1}$		0.723***	0.833***	0.697***	0.803***	0.550***	0.665***
		(7.88)	(7.41)	(5.01)	(5.58)	(3.96)	(4.66)
$IDIO_{t-1}$	0.022***						
	(4.19)						
$CASH_{-1}$	-0.210						
	(-0.89)						
Constant	-1.232**	-0.572***	-0.860***	-1.106***	-1.505***	-1.265***	-1.723***
	(-2.18)	(-2.68)	(-3.30)	(-3.90)	(-4.43)	(-4.54)	(-4.91)
ΔY/ΔX		0.008***	0.008***	0.008***	0.010***	0.007***	0.009***
Year *Industry Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,531	6,530	6,530	6,530	6,530	6,530	6,530
Pseudo R-squared	0.102						
No. of firms		869	869	869	869	869	869

Note: Table 5.B.22 reports the results of Eq. (5.9) to calculate propensity score (Column (I)) and of Eq. (5.1) using the GLM approach with a matched sample. The matching method is kernel matching with the bandwidth of 0.06. The main dependent for probit model (Column (I)) is $SPLIT\_DUM_{t-1}$ that equals one if firms are split rated at time $t-1$ and zero otherwise. The main dependent variables for Column (II) to (VII) are *MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*, which are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable (except for Column (I)) is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time t – 1. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), idiosyncratic risk (*IDIO*), book value of cash over total asset (*CASH*), and taxes over total assets ratio (*TAXES*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.23. Split Ratings (dummy variable) and Capital Structure.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$SPLIT\_DUM_{t-1}$	+	0.022***	0.024***	0.021***	0.028***	0.020***	0.027***
		(5.05)	(4.08)	(4.24)	(3.83)	(4.13)	(3.74)
$TANG_{t-1}$	+	0.050***	0.040**	0.115***	0.127***	0.130***	0.147***
		(3.02)	(2.00)	(5.17)	(4.90)	(6.03)	(5.64)
FS_{t-1}	+	0.023***	0.028***	0.019***	0.029***	0.018***	0.029***
		(7.67)	(7.13)	(4.74)	(5.62)	(4.89)	(5.72)
MTB_{t-1}	-	-0.111***	0.008	-0.062***	0.034***	-0.058***	0.034***
		(-18.70)	(1.00)	(-10.52)	(3.08)	(-9.85)	(3.07)
$PROFIT_{t-1}$	-	-0.164***	0.037	-0.192***	0.017	-0.156**	0.066
		(-3.16)	(0.56)	(-3.05)	(0.20)	(-2.47)	(0.75)
RD_{t-1}	-	-0.290***	-0.472***	-0.205**	-0.402***	-0.199**	-0.404***
		(-3.31)	(-3.71)	(-2.22)	(-2.80)	(-2.16)	(-2.82)
EI_{t-1}	-	-0.008**	-0.006	-0.003	0.004	-0.001	0.008
		(-2.44)	(-1.61)	(-0.75)	(0.76)	(-0.18)	(1.45)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.44)	(2.63)	(0.21)	(0.86)	(0.73)	(1.11)
$INDFL_{t-1}$	+	0.172***	0.192***	0.152***	0.198***	0.130***	0.177***
		(9.23)	(8.40)	(6.22)	(6.48)	(5.74)	(5.86)
Constant		-0.006	-0.099	-0.237	-0.454**	-0.265*	-0.492**
		(-0.04)	(-0.49)	(-1.46)	(-2.12)	(-1.66)	(-2.30)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.600	0.248	0.510	0.306	0.504	0.313
No. of firms		888	888	888	888	888	888

Note: Table 5.B.23 reports the results of Eq. (5.1) using the OLS approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the split dummy variable (*SPLIT_DUM*), which equals to 1 if there are split ratings ($ASPLIT > 0$) at time $t-1$, and 0 otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.24. Split Ratings (dummy variable) and Capital Structure using the Tobit approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$SPLIT\_DUM_{t-1}$	+	0.022***	0.024***	0.021***	0.028***	0.020***	0.027***
		(5.11)	(4.12)	(4.26)	(3.86)	(4.12)	(3.76)
$TANG_{t-1}$	+	0.050***	0.040**	0.116***	0.128***	0.131***	0.148***
		(3.05)	(2.02)	(5.26)	(4.98)	(6.13)	(5.72)
FS_{t-1}	+	0.023***	0.028***	0.019***	0.029***	0.018***	0.030***
		(7.75)	(7.20)	(4.80)	(5.70)	(4.96)	(5.79)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.034***	-0.059***	0.034***
		(-18.90)	(1.01)	(-10.56)	(3.09)	(-9.97)	(3.02)
$PROFIT_{t-1}$	-	-0.164***	0.037	-0.191***	0.018	-0.154**	0.067
		(-3.20)	(0.57)	(-3.03)	(0.21)	(-2.43)	(0.76)
RD_{t-1}	-	-0.290***	-0.472***	-0.217**	-0.413***	-0.214**	-0.418***
		(-3.34)	(-3.75)	(-2.30)	(-2.84)	(-2.25)	(-2.87)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.001	0.008
		(-2.47)	(-1.62)	(-0.70)	(0.78)	(-0.15)	(1.46)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.46)	(2.66)	(0.22)	(0.88)	(0.74)	(1.14)
$INDFL_{t-1}$	+	0.172***	0.192***	0.152***	0.198***	0.131***	0.177***
		(9.33)	(8.49)	(6.27)	(6.54)	(5.79)	(5.92)
Constant		-0.006	-0.099	-0.238	-0.456**	-0.266*	-0.494**
		(-0.04)	(-0.49)	(-1.48)	(-2.15)	(-1.68)	(-2.34)
ΔY*/ΔX		0.021***	0.024**	0.020***	0.027**	0.018**	0.026**
ΔE(Y)/ΔX		0.021***	0.023**	0.018***	0.025**	0.016**	0.024**
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.24 reports the results of Eq. (5.1) using the Tobit approach. The main dependent variables (MDR1, MDR2, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the split dummy variable (*SPLIT_DUM*), which equal to 1 if there are split ratings ($ASPLIT > 0$) at time $t - 1$, and 0 otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.25. Split Ratings (dummy variable) and Capital Structure using the GLM approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$SPLIT\_DUM_{t-1}$	+	0.091***	0.106***	0.110***	0.117***	0.109***	0.116***
		(5.17)	(4.21)	(4.33)	(3.82)	(4.24)	(3.72)
$TANG_{t-1}$	+	0.208***	0.180**	0.555***	0.539***	0.644***	0.630***
		(3.11)	(2.03)	(5.44)	(4.93)	(6.32)	(5.67)
FS_{t-1}	+	0.092***	0.128***	0.081***	0.126***	0.080***	0.128***
		(7.35)	(7.21)	(4.32)	(5.70)	(4.43)	(5.78)
MTB_{t-1}	-	-0.608***	0.039	-0.493***	0.146***	-0.495***	0.148***
		(-22.52)	(1.11)	(-13.69)	(3.10)	(-13.20)	(3.08)
$PROFIT_{t-1}$	-	-0.629***	0.179	-0.964***	0.087	-0.783**	0.304
		(-2.85)	(0.64)	(-3.08)	(0.24)	(-2.42)	(0.81)
RD_{t-1}	-	-1.601***	-1.958***	-1.729***	-1.791***	-1.799***	-1.853***
		(-4.11)	(-3.77)	(-3.16)	(-2.86)	(-3.09)	(-2.87)
EI_{t-1}	-	-0.034**	-0.027*	0.006	0.019	0.022	0.035
		(-2.32)	(-1.67)	(0.26)	(0.81)	(1.03)	(1.51)
AGE_{t-1}	+	0.028**	0.050***	-0.003	0.020	0.007	0.027
		(2.22)	(2.70)	(-0.13)	(0.89)	(0.38)	(1.15)
$INDFL_{t-1}$	+	0.667***	0.845***	0.683***	0.831***	0.605***	0.752***
		(8.78)	(8.45)	(5.89)	(6.50)	(5.36)	(5.90)
Constant		-2.024***	-2.624***	-4.558***	-5.205***	-5.072***	-5.721***
		(-2.93)	(-3.17)	(-6.31)	(-6.08)	(-7.07)	(-6.72)
ΔY/ΔX		0.021***	0.024**	0.021***	0.028**	0.020**	0.027**
		(3.45)	(2.52)	(2.58)	(2.20)	(2.32)	(2.07)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.599	0.246	0.509	0.304	0.503	0.311
No. of firms		888	888	888	888	888	888

Note: Table 5.B.25 reports the results of Eq. (5.1) using the GLM approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the split dummy variable (*SPLIT_DUM*), which equals to 1 if there are split ratings ($ASPLIT > 0$) at time $t-1$, and 0 otherwise. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. Marginal effects of split ratings are presented on row title ΔY/ΔX. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.26. Split Ratings (only split smaller than 0.5 is rounded) and Capital Structure.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT\_R_{t-1}$	+	0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
		(3.58)	(2.40)	(2.67)	(2.22)	(2.39)	(2.10)
$TANG_{t-1}$	+	0.050***	0.040**	0.115***	0.127***	0.130***	0.147***
		(3.01)	(1.99)	(5.15)	(4.89)	(6.00)	(5.63)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.029***	0.018***	0.030***
		(7.70)	(7.14)	(4.75)	(5.63)	(4.91)	(5.73)
MTB_{t-1}	-	-0.111***	0.008	-0.062***	0.034***	-0.058***	0.034***
		(-18.69)	(0.97)	(-10.53)	(3.05)	(-9.86)	(3.04)
$PROFIT_{t-1}$	-	-0.169***	0.032	-0.197***	0.011	-0.160**	0.060
		(-3.23)	(0.48)	(-3.11)	(0.13)	(-2.53)	(0.68)
RD_{t-1}	-	-0.296***	-0.476***	-0.210**	-0.407***	-0.203**	-0.408***
		(-3.37)	(-3.71)	(-2.27)	(-2.81)	(-2.19)	(-2.83)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.000	0.008
		(-2.37)	(-1.54)	(-0.70)	(0.81)	(-0.12)	(1.49)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.48)	(2.68)	(0.25)	(0.91)	(0.77)	(1.15)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.176***
		(9.19)	(8.37)	(6.21)	(6.47)	(5.72)	(5.86)
Constant		0.004	-0.085	-0.226	-0.438**	-0.253	-0.476**
		(0.02)	(-0.42)	(-1.39)	(-2.04)	(-1.58)	(-2.22)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
R-squared		0.599	0.246	0.509	0.304	0.503	0.311
No. of firms		888	888	888	888	888	888

Note: Table 5.B.26 reports the results of Eq. (5.1) using the OLS approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable ($ASPLIT\_R_{t-1}$) is the absolute average of daily differences between Moody's and S&P over a fiscal year (rounded if $ASPLIT\_R < 0$) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.27. Split Ratings (only split smaller than 0.5 is rounded) and Capital Structure using the Tobit approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT\_R_{t-1}$	+	0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
		(3.62)	(2.43)	(2.71)	(2.25)	(2.39)	(2.11)
$TANG_{t-1}$	+	0.050***	0.040**	0.116***	0.128***	0.131***	0.148***
		(3.04)	(2.01)	(5.23)	(4.96)	(6.10)	(5.71)
FS_{t-1}	+	0.024***	0.029***	0.019***	0.030***	0.019***	0.030***
		(7.78)	(7.21)	(4.82)	(5.70)	(4.97)	(5.81)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.034***	-0.059***	0.033***
		(-18.89)	(0.98)	(-10.57)	(3.06)	(-9.98)	(2.99)
$PROFIT_{t-1}$	-	-0.169***	0.032	-0.195***	0.012	-0.158**	0.061
		(-3.27)	(0.48)	(-3.10)	(0.14)	(-2.50)	(0.69)
RD_{t-1}	-	-0.296***	-0.476***	-0.223**	-0.418***	-0.218**	-0.422***
		(-3.41)	(-3.75)	(-2.35)	(-2.85)	(-2.28)	(-2.87)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.000	0.008
		(-2.39)	(-1.55)	(-0.64)	(0.82)	(-0.10)	(1.50)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.51)	(2.71)	(0.26)	(0.92)	(0.78)	(1.18)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.177***
		(9.29)	(8.47)	(6.25)	(6.53)	(5.78)	(5.91)
Constant		0.004	-0.085	-0.227	-0.439**	-0.254	-0.478**
		(0.03)	(-0.42)	(-1.41)	(-2.07)	(-1.61)	(-2.26)
$\Delta Y^*/\Delta X$		0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
$\Delta E(Y)/\Delta X$		0.005***	0.005**	0.004***	0.006**	0.004**	0.005**
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.27 reports the results of Eq. (5.1) using the Tobit approach. The main dependent variables (MDR1, MDR2, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable ($ASPLIT\_R_{t-1}$) is the absolute average of daily differences between Moody's and S&P over a fiscal year (rounded if $ASPLIT\_R_{t-1} < 0$) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title $\Delta Y^*/\Delta X$ shows the marginal effects on the expected value of the censored outcome while row title $\Delta E(Y)/\Delta X$ shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.28. Split Ratings (only split smaller than 0.5 is rounded) and Capital Structure using the GLM approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT\_R_{t-1}$	+	0.022***	0.024**	0.024***	0.025**	0.022**	0.024**
		(3.45)	(2.52)	(2.58)	(2.20)	(2.32)	(2.07)
$TANG_{t-1}$	+	0.209***	0.180**	0.555***	0.539***	0.644***	0.629***
		(3.10)	(2.03)	(5.41)	(4.91)	(6.29)	(5.66)
FS_{t-1}	+	0.093***	0.129***	0.082***	0.127***	0.081***	0.129***
		(7.38)	(7.22)	(4.34)	(5.70)	(4.44)	(5.79)
MTB_{t-1}	-	-0.609***	0.038	-0.494***	0.144***	-0.496***	0.147***
		(-22.50)	(1.08)	(-13.69)	(3.07)	(-13.20)	(3.05)
$PROFIT_{t-1}$	-	-0.645***	0.155	-0.981***	0.062	-0.799**	0.280
		(-2.91)	(0.55)	(-3.12)	(0.17)	(-2.45)	(0.74)
RD_{t-1}	-	-1.624***	-1.978***	-1.745***	-1.811***	-1.811***	-1.869***
		(-4.16)	(-3.78)	(-3.19)	(-2.87)	(-3.11)	(-2.88)
EI_{t-1}	-	-0.033**	-0.026	0.007	0.020	0.024	0.036
		(-2.26)	(-1.60)	(0.31)	(0.85)	(1.07)	(1.55)
AGE_{t-1}	+	0.029**	0.051***	-0.001	0.021	0.009	0.028
		(2.28)	(2.74)	(-0.06)	(0.94)	(0.45)	(1.19)
$INDFL_{t-1}$	+	0.665***	0.844***	0.681***	0.829***	0.602***	0.751***
		(8.74)	(8.43)	(5.86)	(6.49)	(5.34)	(5.89)
Constant		-1.979***	-2.562***	-4.497***	-5.134***	-5.008***	-5.649***
		(-2.86)	(-3.10)	(-6.22)	(-6.00)	(-6.98)	(-6.63)
ΔY/ΔX		0.005***	0.005**	0.005***	0.006**	0.004**	0.006**
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.28 reports the results of Eq. (5.1) using the GLM approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable ($ASPLIT\_R_{t-1}$) is the absolute average of daily differences between Moody's and S&P over a fiscal year (rounded if $ASPLIT\_R_{t-1}$ < 0) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. Marginal effects of split ratings are presented on row title ΔY/ΔX. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.29. Split Ratings and Capital Structure (excluding missing *xrd*).

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.007***	0.006*	0.007***	0.009**	0.007***	0.009**
		(3.20)	(1.68)	(2.88)	(2.15)	(2.81)	(2.19)
$TANG_{t-1}$	+	0.071**	0.049	0.157***	0.177***	0.173***	0.199***
		(2.43)	(1.36)	(4.53)	(4.11)	(5.31)	(4.71)
FS_{t-1}	+	0.029***	0.030***	0.025***	0.032***	0.022***	0.030***
		(6.59)	(4.68)	(4.78)	(4.24)	(4.63)	(4.01)
MTB_{t-1}	-	-0.103***	0.004	-0.062***	0.016	-0.058***	0.015
		(-13.82)	(0.35)	(-8.52)	(1.14)	(-8.19)	(1.07)
$PROFIT_{t-1}$	-	-0.160*	0.020	-0.126	0.114	-0.114	0.135
		(-1.96)	(0.17)	(-1.28)	(0.79)	(-1.20)	(0.94)
RD_{t-1}	-	-0.509***	-0.776***	-0.401***	-0.679***	-0.389***	-0.681***
		(-4.44)	(-4.66)	(-3.41)	(-3.60)	(-3.32)	(-3.63)
EI_{t-1}	-	-0.011***	-0.008*	-0.007	-0.002	-0.005	0.001
		(-2.90)	(-1.84)	(-1.61)	(-0.35)	(-1.25)	(0.21)
AGE_{t-1}	+	0.008*	0.014**	0.004	0.014*	0.007	0.015*
		(1.81)	(2.11)	(0.63)	(1.66)	(1.36)	(1.96)
$INDFL_{t-1}$	+	0.099***	0.144***	0.059*	0.114**	0.037	0.091**
		(3.69)	(4.25)	(1.78)	(2.54)	(1.26)	(2.12)
Constant		0.441***	0.282***	-0.349***	-0.617***	-0.327***	-0.605***
		(7.67)	(3.26)	(-5.02)	(-5.93)	(-5.07)	(-5.84)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		3,365	3,365	3,365	3,365	3,365	3,365
R-squared		0.618	0.264	0.525	0.322	0.529	0.333
No. of firms		451	451	451	451	451	451

Note: Table 5.B.29 reports the results of Eq. (5.1) using the OLS approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (excluding missing *xrd*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.30. Split Ratings and Capital Structure using the Tobit approach (excluding missing *xrd*).

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.007***	0.006*	0.007***	0.009**	0.007***	0.009**
		(3.25)	(1.71)	(2.96)	(2.22)	(2.84)	(2.23)
$TANG_{t-1}$	+	0.071**	0.049	0.158***	0.178***	0.175***	0.201***
		(2.47)	(1.39)	(4.65)	(4.21)	(5.45)	(4.83)
FS_{t-1}	+	0.029***	0.030***	0.025***	0.033***	0.022***	0.030***
		(6.70)	(4.77)	(4.85)	(4.31)	(4.68)	(4.07)
MTB_{t-1}	-	-0.103***	0.004	-0.062***	0.016	-0.060***	0.015
		(-14.06)	(0.35)	(-8.58)	(1.16)	(-8.28)	(1.03)
$PROFIT_{t-1}$	-	-0.160**	0.020	-0.128	0.111	-0.115	0.133
		(-1.99)	(0.17)	(-1.30)	(0.78)	(-1.21)	(0.92)
RD_{t-1}	-	-0.509***	-0.776***	-0.421***	-0.701***	-0.411***	-0.707***
		(-4.52)	(-4.74)	(-3.48)	(-3.65)	(-3.41)	(-3.69)
EI_{t-1}	-	-0.011***	-0.008*	-0.007	-0.002	-0.005	0.002
		(-2.95)	(-1.87)	(-1.53)	(-0.31)	(-1.19)	(0.24)
AGE_{t-1}	+	0.008*	0.014**	0.004	0.014*	0.007	0.016**
		(1.84)	(2.15)	(0.66)	(1.69)	(1.39)	(2.01)
$INDFL_{t-1}$	+	0.099***	0.144***	0.058*	0.113**	0.036	0.091**
		(3.75)	(4.33)	(1.78)	(2.56)	(1.27)	(2.14)
Constant		0.441***	0.282***	-0.352***	-0.621***	-0.329***	-0.609***
		(7.80)	(3.32)	(-5.14)	(-6.06)	(-5.18)	(-5.96)
ΔY*/ΔX		0.006***	0.005*	0.007***	0.009**	0.006***	0.009**
ΔE(Y)/ΔX		0.006***	0.005*	0.006***	0.008**	0.006***	0.008**
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		3,365	3,365	3,365	3,365	3,365	3,365
No. of firms		451	451	451	451	451	451

Note: Table 5.B.30 reports the results of Eq. (5.1) using the Tobit approach. The main dependent variables (MDR1, MDR2, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (excluding missing *xrd*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.31. Split Ratings and Capital Structure using the GLM approach (excluding missing *xrd*).

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.027***	0.025*	0.036**	0.038**	0.036**	0.039**
		(3.05)	(1.81)	(2.55)	(2.19)	(2.47)	(2.22)
$TANG_{t-1}$	+	0.304***	0.238	0.791***	0.775***	0.901***	0.884***
		(2.61)	(1.48)	(5.02)	(4.25)	(6.00)	(4.90)
FS_{t-1}	+	0.114***	0.133***	0.113***	0.144***	0.097***	0.136***
		(6.23)	(4.81)	(4.22)	(4.37)	(3.89)	(4.14)
MTB_{t-1}	-	-0.592***	0.020	-0.556***	0.070	-0.581***	0.065
		(-16.50)	(0.43)	(-11.24)	(1.15)	(-11.27)	(1.05)
$PROFIT_{t-1}$	-	-0.501	0.089	-0.490	0.539	-0.403	0.664
		(-1.42)	(0.18)	(-0.91)	(0.86)	(-0.74)	(1.05)
RD_{t-1}	-	-2.429***	-3.248***	-2.587***	-3.069***	-2.669***	-3.186***
		(-4.68)	(-4.75)	(-3.63)	(-3.69)	(-3.53)	(-3.72)
EI_{t-1}	-	-0.053***	-0.038*	-0.036	-0.010	-0.020	0.007
		(-2.99)	(-1.95)	(-1.19)	(-0.34)	(-0.64)	(0.25)
AGE_{t-1}	+	0.033*	0.062**	0.017	0.059*	0.035	0.068**
		(1.79)	(2.17)	(0.52)	(1.68)	(1.27)	(2.00)
$INDFL_{t-1}$	+	0.377***	0.640***	0.256	0.473**	0.143	0.380**
		(3.50)	(4.33)	(1.53)	(2.53)	(0.93)	(2.09)
Constant		0.052	-0.880**	-7.445***	-8.543***	-8.055***	-9.244***
		(0.22)	(-2.34)	(-21.26)	(-18.94)	(-23.85)	(-20.13)
ΔY/ΔX		0.006***	0.006*	0.006**	0.009**	0.006**	0.009**
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		3,365	3,365	3,365	3,365	3,365	3,365
No. of firms		451	451	451	451	451	451

Note: Table 5.B.31 reports the results of Eq. (5.1) using the GLM approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (excluding missing *xrd*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. Marginal effects of split ratings are presented on row title ΔY/ΔX. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.32. Split Ratings and Capital Structure (excluding financial (SIC 6000 – 6999) and utility firms (SIC 4900 – 4999)).

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.006***	0.005**	0.005**	0.006**	0.004**	0.006*
		(3.51)	(2.29)	(2.50)	(2.09)	(2.21)	(1.94)
$TANG_{t-1}$	+	0.043**	0.036*	0.102***	0.115***	0.121***	0.138***
		(2.43)	(1.67)	(4.25)	(4.07)	(5.21)	(4.89)
FS_{t-1}	+	0.025***	0.029***	0.018***	0.029***	0.017***	0.028***
		(7.25)	(6.26)	(4.15)	(4.73)	(4.16)	(4.71)
MTB_{t-1}	-	-0.107***	0.013	-0.062***	0.035***	-0.057***	0.035***
		(-18.20)	(1.52)	(-10.60)	(3.09)	(-9.89)	(3.07)
$PROFIT_{t-1}$	-	-0.133**	0.039	-0.152**	0.036	-0.120*	0.082
		(-2.52)	(0.57)	(-2.40)	(0.41)	(-1.88)	(0.92)
RD_{t-1}	-	-0.351***	-0.504***	-0.244**	-0.412***	-0.224**	-0.400***
		(-3.92)	(-3.81)	(-2.56)	(-2.72)	(-2.34)	(-2.65)
EI_{t-1}	-	-0.007**	-0.004	-0.003	0.004	-0.001	0.008
		(-2.29)	(-1.15)	(-0.87)	(0.81)	(-0.23)	(1.56)
AGE_{t-1}	+	0.007*	0.011**	-0.001	0.004	0.002	0.005
		(1.96)	(2.28)	(-0.21)	(0.59)	(0.38)	(0.87)
$INDFL_{t-1}$	+	0.150***	0.185***	0.140***	0.203***	0.123***	0.185***
		(6.95)	(6.85)	(5.07)	(5.74)	(4.75)	(5.31)
Constant		0.032	-0.057	-0.180	-0.389*	-0.213	-0.431**
		(0.19)	(-0.28)	(-1.10)	(-1.80)	(-1.32)	(-2.00)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		5,880	5,880	5,880	5,880	5,880	5,880
R-squared		0.580	0.232	0.489	0.287	0.483	0.294
No. of firms		797	797	797	797	797	797

Note: Table 5.B.32 reports the results of Eq. (5.1) using the OLS approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The sample excludes financial firms (SIC codes: 6000 – 6999) and utility firms (SIC codes: 4900 – 4999). The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.33. Split Ratings and Capital Structure using the Tobit approach (excluding financial (SIC 6000 – 6999) and utility firms (SIC 4900 – 4999)).

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.006***	0.005**	0.005**	0.006**	0.004**	0.006*
		(3.55)	(2.31)	(2.54)	(2.12)	(2.20)	(1.95)
$TANG_{t-1}$	+	0.043**	0.036*	0.103***	0.116***	0.122***	0.140***
		(2.46)	(1.69)	(4.33)	(4.14)	(5.30)	(4.97)
FS_{t-1}	+	0.025***	0.029***	0.018***	0.029***	0.017***	0.029***
		(7.33)	(6.33)	(4.20)	(4.80)	(4.21)	(4.78)
MTB_{t-1}	-	-0.107***	0.013	-0.062***	0.035***	-0.058***	0.035***
		(-18.40)	(1.54)	(-10.62)	(3.10)	(-9.97)	(3.02)
$PROFIT_{t-1}$	-	-0.133**	0.039	-0.151**	0.037	-0.118*	0.083
		(-2.54)	(0.58)	(-2.38)	(0.42)	(-1.86)	(0.93)
RD_{t-1}	-	-0.351***	-0.504***	-0.256***	-0.424***	-0.238**	-0.415***
		(-3.96)	(-3.85)	(-2.63)	(-2.76)	(-2.42)	(-2.70)
EI_{t-1}	-	-0.007**	-0.004	-0.003	0.005	-0.001	0.008
		(-2.32)	(-1.16)	(-0.81)	(0.83)	(-0.19)	(1.57)
AGE_{t-1}	+	0.007**	0.011**	-0.001	0.004	0.002	0.006
		(1.98)	(2.31)	(-0.20)	(0.60)	(0.40)	(0.90)
$INDFL_{t-1}$	+	0.150***	0.185***	0.140***	0.203***	0.124***	0.187***
		(7.02)	(6.93)	(5.11)	(5.79)	(4.82)	(5.37)
Constant		0.032	-0.057	-0.182	-0.391*	-0.214	-0.434**
		(0.19)	(-0.28)	(-1.11)	(-1.82)	(-1.35)	(-2.04)
ΔY*/ΔX		0.006***	0.005**	0.005***	0.006**	0.004**	0.006*
ΔE(Y)/ΔX		0.006***	0.005**	0.004***	0.006**	0.004**	0.005*
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		5,880	5,880	5,880	5,880	5,880	5,880
No. of firms		797	797	797	797	797	797

Note: Table 5.B.33 reports the results of Eq. (5.1) using the Tobit approach. The main dependent variables (MDR1, MDR2, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The sample excludes financial firms (SIC codes: 6000 – 6999) and utility firms (SIC codes: 4900 – 4999). The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.34. Split Ratings and Capital Structure using the GLM approach (excluding financial (SIC 6000 – 6999) and utility firms (SIC 4900 – 4999)).

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.024***	0.025**	0.025**	0.026**	0.022**	0.025*
		(3.38)	(2.41)	(2.35)	(2.07)	(2.05)	(1.92)
$TANG_{t-1}$	+	0.179**	0.166*	0.490***	0.491***	0.594***	0.595***
		(2.48)	(1.75)	(4.37)	(4.12)	(5.32)	(4.93)
FS_{t-1}	+	0.098***	0.131***	0.082***	0.124***	0.079***	0.125***
		(6.86)	(6.33)	(3.77)	(4.80)	(3.74)	(4.78)
MTB_{t-1}	-	-0.587***	0.058	-0.491***	0.150***	-0.493***	0.153***
		(-21.51)	(1.60)	(-13.43)	(3.12)	(-12.88)	(3.11)
$PROFIT_{t-1}$	-	-0.498**	0.180	-0.766**	0.166	-0.590*	0.377
		(-2.22)	(0.62)	(-2.39)	(0.45)	(-1.78)	(0.98)
RD_{t-1}	-	-1.815***	-2.098***	-1.840***	-1.820***	-1.848***	-1.829***
		(-4.54)	(-3.87)	(-3.25)	(-2.77)	(-3.07)	(-2.70)
EI_{t-1}	-	-0.031**	-0.019	0.002	0.020	0.022	0.038
		(-2.09)	(-1.20)	(0.10)	(0.86)	(0.92)	(1.62)
AGE_{t-1}	+	0.026*	0.049**	-0.011	0.016	0.002	0.024
		(1.80)	(2.35)	(-0.48)	(0.62)	(0.10)	(0.91)
$INDFL_{t-1}$	+	0.594***	0.815***	0.653***	0.854***	0.591***	0.793***
		(6.70)	(6.92)	(4.83)	(5.77)	(4.45)	(5.35)
Constant		-1.884***	-2.419***	-4.352***	-4.940***	-4.891***	-5.477***
		(-2.71)	(-2.90)	(-5.93)	(-5.71)	(-6.76)	(-6.37)
ΔY/ΔX		0.005***	0.006**	0.005**	0.006**	0.004**	0.006*
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		5,880	5,880	5,880	5,880	5,880	5,880
No. of firms		797	797	797	797	797	797

Note: Table 5.B.34 reports the results of Eq. (5.1) using the GLM approach. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The sample excludes financial firms (SIC codes: 6000 – 6999) and utility firms (SIC codes: 4900 – 4999). The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time *t – 1*. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. Marginal effects of split ratings are presented on row title ΔY/ΔX. The regressions include rating level dummies and Year*Industry interacting fixed effects. Numbers in parentheses are robust z-statistics. Standard errors are clustered at firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.35. Superior S&P ratings and superior Moody's ratings with the Tobit approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
SUP_MOODY_{t-1}	+	0.025***	0.026***	0.020***	0.025***	0.017**	0.021**
		(4.40)	(3.40)	(2.83)	(2.58)	(2.47)	(2.11)
$SUP\_S\&P_{t-1}$	+	0.016***	0.020***	0.017***	0.024***	0.016***	0.024***
		(3.63)	(3.18)	(3.12)	(3.08)	(3.06)	(3.11)
$TANG_{t-1}$	+	0.050***	0.040**	0.116***	0.128***	0.131***	0.148***
		(3.05)	(2.02)	(5.25)	(4.97)	(6.11)	(5.72)
FS_{t-1}	+	0.023***	0.028***	0.019***	0.030***	0.018***	0.030***
		(7.77)	(7.20)	(4.80)	(5.69)	(4.95)	(5.79)
MTB_{t-1}	-	-0.111***	0.008	-0.063***	0.034***	-0.059***	0.034***
		(-18.92)	(1.01)	(-10.57)	(3.09)	(-9.97)	(3.02)
$PROFIT_{t-1}$	-	-0.166***	0.035	-0.194***	0.014	-0.157**	0.062
		(-3.22)	(0.54)	(-3.07)	(0.16)	(-2.48)	(0.70)
RD_{t-1}	-	-0.287***	-0.470***	-0.215**	-0.412***	-0.212**	-0.417***
		(-3.27)	(-3.72)	(-2.27)	(-2.81)	(-2.22)	(-2.84)
EI_{t-1}	-	-0.008**	-0.006	-0.002	0.004	-0.000	0.008
		(-2.50)	(-1.64)	(-0.70)	(0.78)	(-0.14)	(1.47)
AGE_{t-1}	+	0.008**	0.011***	0.001	0.005	0.003	0.006
		(2.48)	(2.68)	(0.24)	(0.90)	(0.77)	(1.17)
$INDFL_{t-1}$	+	0.172***	0.191***	0.151***	0.198***	0.130***	0.177***
		(9.30)	(8.46)	(6.25)	(6.52)	(5.78)	(5.91)
Constant		0.005	-0.087	-0.226	-0.440**	-0.254*	-0.478**
		(0.03)	(-0.45)	(-1.46)	(-2.16)	(-1.66)	(-2.34)
ΔY*/ΔX(*SUP_MOODY*)		0.025***	0.026***	0.018***	0.025***	0.016**	0.021**
ΔY*/ΔX(*SUP_S&P*)		0.016***	0.020***	0.016***	0.023***	0.015***	0.023***
ΔE(Y)/ΔX(*SUP_MOODY*)		0.024***	0.025***	0.017***	0.023***	0.014**	0.019**
ΔE(Y)/ΔX(*SUP_S&P*)		0.016***	0.019***	0.014***	0.022***	0.014***	0.021***
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.35 reports the results of Eq. (5.1) using the Tobit approach with two dummy variables, SUP_MOODY_{t-1} and $SUP\_S\&P_{t-1}$. The main independent variables are *SUP_MOODY* and *SUP_S&P*, where *SUP_MOODY* (*SUP_S&P*) is a dummy variable equal to 1 if Moody's (S&P) rating is higher. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Row title ΔY*/ΔX shows the marginal effects on the expected value of the censored outcome while row title ΔE(Y)/ΔX shows the marginal effects on the expected value of the truncated outcome. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.B.36. Superior S&P ratings and superior Moody's ratings with the GLM approach.

Variables	Expected sign	*MDR1* (I)	*BDR1* (II)	*MDR2* (III)	*BDR2* (IV)	*MDR3* (V)	*BDR3* (VI)
SUP_MOODY_{t-1}	+	0.109***	0.115***	0.103***	0.107***	0.092***	0.092**
		(4.59)	(3.40)	(2.96)	(2.60)	(2.58)	(2.13)
$SUP\_S\&P_{t-1}$	+	0.067***	0.087***	0.085***	0.100***	0.088***	0.102***
		(3.57)	(3.26)	(3.17)	(3.05)	(3.17)	(3.09)
$TANG_{t-1}$	+	0.208***	0.180**	0.556***	0.540***	0.645***	0.631***
		(3.10)	(2.03)	(5.43)	(4.92)	(6.31)	(5.66)
FS_{t-1}	+	0.093***	0.128***	0.081***	0.126***	0.080***	0.129***
		(7.37)	(7.20)	(4.32)	(5.69)	(4.43)	(5.78)
MTB_{t-1}	-	-0.608***	0.039	-0.493***	0.145***	-0.495***	0.148***
		(-22.57)	(1.10)	(-13.71)	(3.10)	(-13.20)	(3.07)
$PROFIT_{t-1}$	-	-0.632***	0.171	-0.978***	0.070	-0.800**	0.282
		(-2.87)	(0.61)	(-3.11)	(0.19)	(-2.46)	(0.75)
RD_{t-1}	-	-1.600***	-1.950***	-1.724***	-1.783***	-1.792***	-1.846***
		(-4.06)	(-3.74)	(-3.13)	(-2.83)	(-3.06)	(-2.85)
EI_{t-1}	-	-0.035**	-0.027*	0.005	0.019	0.023	0.035
		(-2.36)	(-1.69)	(0.25)	(0.81)	(1.03)	(1.53)
AGE_{t-1}	+	0.028**	0.050***	-0.002	0.021	0.008	0.027
		(2.23)	(2.71)	(-0.09)	(0.92)	(0.42)	(1.18)
$INDFL_{t-1}$	+	0.666***	0.844***	0.683***	0.830***	0.604***	0.751***
		(8.76)	(8.42)	(5.87)	(6.48)	(5.35)	(5.89)
Constant		-1.977***	-2.569***	-4.493***	-5.137***	-5.005***	-5.651***
		(-3.04)	(-3.26)	(-6.55)	(-6.27)	(-7.31)	(-6.88)
ΔY/ΔX(*SUP_MOODY*)		0.025***	0.026***	0.020***	0.025***	0.017***	0.021**
ΔY/ΔX(*SUP_S&P*)		0.015***	0.020***	0.016***	0.023***	0.016***	0.024***
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
No. of firms		888	888	888	888	888	888

Note: Table 5.B.36 reports the results of Eq. (5.1) using the GLM approach with two interaction term, SUP_MOODY_{t-1} and $SUP\_S\&P_{t-1}$. The main independent variables are *SUP_MOODY* and *SUP_S&P*, where *SUP_MOODY* (*SUP_S&P*) is dummy variable equal to 1 if Moody's (S&P) rating is higher. The main dependent variables (*MDR1*, *MDR2*, *MDR3*, *BDR1*, *BDR2*, and *BDR3*) are measured as the ratio of debt over debt plus market/book value of equity. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*), see Table 5.1 for definitions. The regressions include rating level dummies and Year*Industry interacting fixed effects. Marginal effects of split ratings are presented on row title ΔY/ΔX. Numbers in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix 5.C Superior Rating Model, Inferior Rating Model and Capital Structure

Similar to Appendix 3.D of Chapter 3, the superior rating model and inferior rating model are employed to test whether the information risk arising from split ratings has a distinct effect from the credit risk arising from the rating level.

$$\begin{aligned} RATIO_{i,t} = {} & \beta_0 + \beta_S ASPLIT_{i,t-1} \\ & + \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} SUP\_LEVEL_{i,k,t-1} \\ & + \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \end{aligned} \tag{5.C.1}$$

$$\begin{aligned} RATIO_{i,t} = {} & \beta_0 + \beta_I ASPLIT_{i,t-1} \\ & + \gamma_j \sum_{j=1}^{8} CONTROL_{i,j,t-1} + \lambda_k \sum_{k=1}^{19} INF\_LEVEL_{i,k,t-1} \\ & + \varphi_{l,m} \sum_{l=1}^{13} \sum_{m=1}^{8} YEAR_{i,l,t} \times INDUSTRY_{i,m,t} + \varepsilon_{i,t} \end{aligned} \tag{5.C.2}$$

The empirical results of the two regression models are illustrated in Figure 5.C.1. Since β_S is positive and β_I is negative, the actual level of leverage of split rated firms lies in between the estimated level of leverage of these firms if CRAs had assigned the same inferior and superior rating levels.

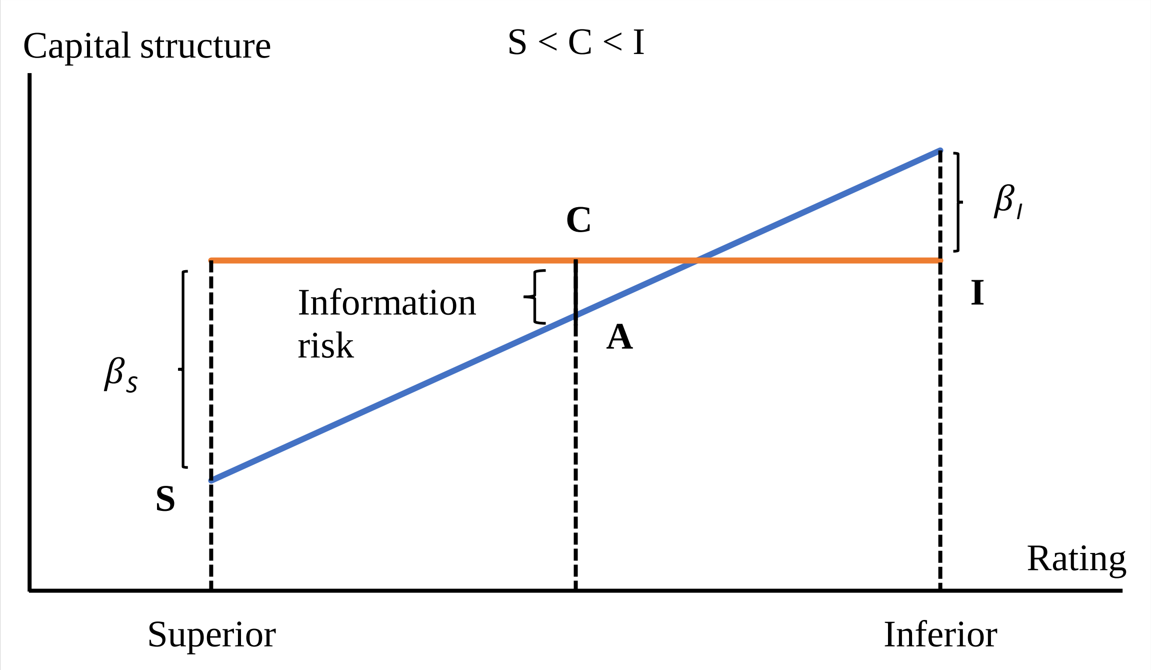

Figure 5.C.1. Illustration of information risk, credit risk and capital structure
I is the estimated debt maturity level on split rated firms if both CRAs had assigned the same inferior rating. *S* is the estimated debt maturity level on split rated firms if both CRAs had assigned the same superior rating. *A* is the average of *I* and *S*. *C* is the actual debt maturity level of the split rated firms. The difference between *C* and *A* is the information risk arising from split ratings.

Tables 5.C.1 and 5.C.2 report the results of two rating models with market and book leverage ratios. In the superior rating model, the coefficients for *ASPLIT* (β_S) for market capital structure ratios (*MDR1*, *MDR2* and *MDR3*) are positive and significant, suggesting that an inferior rating significantly increases the level of the market leverage of split rated firms. The level of market leverage for one-notch split rated firms is typically 2.4% (i.e., 3 × 0.008 = 0.024) higher when compared to the estimated capital structure level for these firms if both CRAs had assigned the same superior ratings level. In the inferior rating model, the coefficient for *ASPLIT* (β_I) for market capital structure ratios (*MDR1*, *MDR2* and *MDR3*) are negative and marginally significant (for *MDR2* and *MDR3*), suggesting that a superior rating decreases the level of the market leverage of split rated firms. Because the coefficients for *ASPLIT* in both the superior model and the inferior model are positive and significant, the actual debt maturity level of split rated firms are lying within the estimated level of these firms if both CRAs had assigned the same superior or inferior ratings level (as illustrated in Figure 5.C.1).

The information risk is about 0.9% (i.e., (0.024 – 0.06)/2 = 0.009) for *MDR1* and 0.6% (i.e., (0.024 - 0.012)/2 = 0.006) for *MDR2* and *MDR3*, suggesting that firms with split ratings have on average, a higher level of market capital structure than the average of estimated capital structure of these firms if CRAs had assigned both superior and inferior ratings levels. This also suggests that apart from the credit risk, firms' managers consider split ratings as an extra source of risk (information risk) when assessing the optimal capital structure level and they rely more on debt financing than equity financing when split ratings occur. Thus, the result is consistent with the baseline model.

Table 5.C.1. Market capital structure, superior rating model and inferior rating model

Variables	Expected sign	Superior Rating Model *MDR1* (I)	*MDR2* (II)	*MDR3* (III)	Inferior Rating Model *MDR1* (IV)	*MDR2* (V)	*MDR3* (VI)
$ASPLIT_{t-1}$	+	0.008***	0.008***	0.008***	-0.002	-0.004*	-0.004**
		(5.33)	(4.36)	(4.08)	(-1.15)	(-1.82)	(-2.24)
$TANG_{t-1}$	+	0.046***	0.110***	0.124***	0.050***	0.116***	0.130***
		(2.87)	(5.06)	(5.92)	(3.04)	(5.35)	(6.20)
FS_{t-1}	+	0.025***	0.021***	0.020***	0.024***	0.019***	0.019***
		(8.19)	(5.29)	(5.46)	(7.87)	(4.88)	(5.05)
MTB_{t-1}	-	-0.112***	-0.063***	-0.058***	-0.110***	-0.062***	-0.057***
		(-18.45)	(-10.40)	(-9.76)	(-18.64)	(-10.43)	(-9.83)
$PROFIT_{t-1}$	-	-0.133**	-0.147**	-0.110*	-0.163***	-0.180***	-0.139**
		(-2.51)	(-2.30)	(-1.74)	(-3.12)	(-2.85)	(-2.21)
RD_{t-1}	-	-0.297***	-0.223**	-0.219**	-0.293***	-0.204**	-0.197**
		(-3.39)	(-2.42)	(-2.36)	(-3.38)	(-2.23)	(-2.14)
EI_{t-1}	-	-0.008**	-0.004	-0.002	-0.008**	-0.002	-0.000
		(-2.57)	(-1.06)	(-0.46)	(-2.53)	(-0.69)	(-0.14)
AGE_{t-1}	+	0.008**	0.001	0.003	0.008**	0.001	0.003
		(2.51)	(0.21)	(0.76)	(2.56)	(0.24)	(0.74)
$INDFL_{t-1}$	+	0.174***	0.155***	0.134***	0.171***	0.150***	0.129***
		(9.30)	(6.39)	(5.94)	(9.18)	(6.15)	(5.66)
Constant		-0.239***	-0.451***	-0.475***	0.161*	-0.092	-0.124
		(-6.73)	(-9.78)	(-10.52)	(1.89)	(-1.10)	(-1.55)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
Adjusted R-squared		0.606	0.521	0.515	0.604	0.517	0.511
No. of firms		888	888	888	888	888	888

Note: Table 5.C.1 reports the results of Eq. (5.C.1) and (5.C.2) using OLS estimation. The main dependent variables (*MDR1*, *MDR2* and *MDR3*) are measured as the ratio of debt over debt plus market value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*). See Table 5.1 for definitions. In the Superior (Inferior) Rating Model, the superior (inferior) rating of split rated firms are used to construct the rating dummy variables. The regressions include Year*Industry interacting fixed effects. Values in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5.C.2. Book capital structure, superior rating model and inferior rating model

Variables	Expected sign	Superior Rating Model			Inferior Rating Model		
		BDR1 (I)	*BDR2* (II)	*BDR3* (III)	*BDR1* (IV)	*BDR2* (V)	*BDR3* (VI)
$ASPLIT_{t-1}$	+	0.008***	0.010***	0.010***	-0.002	-0.005*	-0.006*
		(3.67)	(3.68)	(3.57)	(-1.04)	(-1.66)	(-1.95)
$TANG_{t-1}$	+	0.035*	0.119***	0.138***	0.037*	0.125***	0.144***
		(1.76)	(4.61)	(5.34)	(1.84)	(4.84)	(5.56)
FS_{t-1}	+	0.030***	0.032***	0.032***	0.030***	0.031***	0.031***
		(7.46)	(6.08)	(6.18)	(7.36)	(5.91)	(6.00)
MTB_{t-1}	-	0.008	0.033***	0.034***	0.012	0.038***	0.037***
		(0.90)	(2.98)	(3.03)	(1.44)	(3.48)	(3.40)
$PROFIT_{t-1}$	-	0.071	0.072	0.123	0.039	0.033	0.087
		(1.06)	(0.83)	(1.39)	(0.58)	(0.38)	(0.99)
RD_{t-1}	-	-0.470***	-0.411***	-0.418***	-0.472***	-0.401***	-0.403***
		(-3.72)	(-2.87)	(-2.95)	(-3.79)	(-2.86)	(-2.89)
EI_{t-1}	-	-0.006	0.004	0.008	-0.006	0.005	0.008
		(-1.46)	(0.72)	(1.44)	(-1.46)	(0.93)	(1.57)
AGE_{t-1}	+	0.011***	0.004	0.006	0.011***	0.005	0.006
		(2.66)	(0.83)	(1.11)	(2.70)	(0.89)	(1.12)
$INDFL_{t-1}$	+	0.193***	0.201***	0.180***	0.191***	0.197***	0.176***
		(8.39)	(6.57)	(6.00)	(8.44)	(6.49)	(5.88)
Constant		-0.389***	-0.743***	-0.782***	0.013	-0.330***	-0.363***
		(-8.82)	(-12.59)	(-13.17)	(0.12)	(-2.58)	(-2.84)
Year *Industry Interactions		Yes	Yes	Yes	Yes	Yes	Yes
Rating Level Dummies		Yes	Yes	Yes	Yes	Yes	Yes
Observations		6,684	6,684	6,684	6,684	6,684	6,684
Adjusted R-squared		0.257	0.317	0.327	0.253	0.315	0.322
No. of firms		888	888	888	888	888	888

Note: Table 5.C.2 reports the results of Eq. (5.C.1) and Eq. (5.C.2) using OLS estimation. The main dependent variables (*BDR1*, *BDR2* and *BDR3*) are measured as the ratio of debt over debt plus book value of equity. The main independent variable is the rounded value of the absolute average of daily differences between Moody's and S&P over a fiscal year (*ASPLIT*) at time $t-1$. The control variables are asset tangibility (*TANG*), firm size (*FS*), market-to-book ratio (*MTB*), profitability (*PROFIT*), ratio of R&D over sales (*RD*), equity issues (*EI*), the natural logarithm of firm age (*AGE*), and the median industry leverage (*INDFL*). See Table 5.1 for definitions. In the Superior (Inferior) Rating Model, the superior (inferior) ratings of split rated firms are used to construct the rating dummy variables. The regressions include Year*Industry interacting fixed effects. Values in parentheses are robust t-statistics. Standard errors are clustered at firm level. The data sample is explained in Table 5.2. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Chapter 6: Conclusion

Credit rating agencies (CRAs) have been subject to considerable attention from regulators and the public during and after the U.S. sub-prime crisis from 2007 to 2008 and the European financial crisis from 2009 to 2012. In the U.S., firms solicit credit ratings from at least two major CRAs, Moody's and S&P, in order to maximise their access to the capital markets. However, CRAs disagree with each other about U.S. firms' creditworthiness for a majority of the observed cases. Regulators and academic researchers often treat CRAs' opinions as being equal whereas considerable differences exist. The main aim of this thesis is to investigate the effect of CRAs' disagreement about U.S. firms' creditworthiness on these firms' cost of capital, capital structure and debt maturity structure.

In order to investigate the impact of split ratings on investors' behaviour and firms' behaviour regarding debt maturity and capital structure choices, the thesis uses different methodologies, including cross-sectional models, estimation with OLS, GLM, Tobit and PSM. Additionally, within the PSM methodology, various matching methods including nearest neighbour, caliper, radius, kernel and Mahalanobis matching are employed. The thesis uses a recent sample of all U.S. corporations rated by Moody's and S&P from 2003 to 2015 (2017 for Chapter 3). The thesis also employs cross-sectional models to investigate whether the impact of split ratings varies across different types of firms or time periods (small vs large firms, investment-grade vs speculative-grade firms and crisis vs non-crisis periods). Additionally, the thesis investigates whether superior ratings from one CRA have a different impact on the behaviour of investors and firms compared to superior ratings from the other CRA. This provides insights into whether investors and firms' managers have a preference for a given CRA.

The thesis finds that CRAs' different opinions about firms' creditworthiness have a significant impact on equity investors as well as firms' debt maturity and capital structure decisions. The thesis' findings suggest that equity investors and firms' managers take into account the information asymmetry risk arising from split ratings and that investors require a premium, while firms adjust their optimal level of debt maturity and capital structure. Additionally, the thesis finds that the impact of split ratings on debt maturity and capital structure tends to be more prominent with large firms, while the impact of split ratings on the cost of equity capital is more prominent with small firms. The effect of split ratings on the cost of equity and debt maturity is stronger for speculative-grade firms, while the effect of split ratings on capital structure is stronger for investment-grade firms. The thesis also finds that investors and firms' managers have different preferences with regards to CRAs when considering the credit quality or the default risk of these firms. Equity investors tend to place more emphasize on S&P ratings. On the other hand, firms' managers tend to place more weight on Moody's rating when deciding on their debt maturity. For capital structure decisions, there is no evidence that firms' managers differentiate between split ratings with superior Moody's ratings and split ratings with superior S&P ratings. Finally, employing matching methods enables the separation of the information asymmetry risk arising from split ratings from the information asymmetry risk arising from other sources.[82] All of the results and inferences based on PSM are similar to the main results. Therefore, the thesis highlights the effect of information asymmetry, which is specifically related to credit risk after controlling for other factors related to information asymmetry that might affect equity investors or firms' managers. The next paragraph will provide further details on the findings of each empirical chapter of the thesis.

Chapter 3 employs a cross-sectional model to generate forecast earnings as well as the cost of equity capital. Chapters 4 and 5 apply the Tobit and GLM models alongside OLS estimation in order to address any potential issues with proportional dependent variables such as debt maturity and capital structure. Additionally, each of the three chapters employs propensity score matching (PSM) with various matching methods, namely, nearest neighbour matching, caliper matching, radius matching, kernel matching and Mahalanobis matching, to mitigate any potential endogeneity issue. Further robustness tests are included as appropriate.

Chapter 3 examines the first research question: 'What is the impact of split ratings on the cost of equity capital?'. The main sample consists of 820 U.S. corporations rated by Moody's and S&P from 2003 to 2017. The impact of split ratings on firms' cost of equity capital is examined using various methods, including ordinary least squares (OLS) estimation and propensity score matching (PSM). Split ratings are indicative of information opaqueness and/or information asymmetry problems (see, Morgan, 2002; Livingston et al., 2010). It is proposed that sophisticated equity investors recognise the ambiguity surrounding firms' creditworthiness and charge firms a premium on the cost of capital in order to compensate for this.

[82] The aim of the PSM method is to create a sample of treated group (split rated firms) and untreated group (non-split rated firms) with similar characteristics (covariates). Thus, the occurrence of split ratings in the matching sample are randomized given the balance covariates (in this case, factors related to information asymmetry such as firm size or idiosyncratic risk).

The results of Chapter 3 suggest that split rated firms on average have a higher cost of equity capital than their non-split rated peers with similar credit risk. This indicates that equity investors recognise the ambiguity surrounding split rated firms' creditworthiness and charge them a premium for that uncertainty. The results are more pronounced among small firms and those with speculative-grade ratings. Arguably, these types of firms are more sensitive to any doubts or negativity about their creditworthiness. Thus, the findings of Chapter 3 suggest that split ratings bring new information about firms' creditworthiness to the equity market. This is consistent with the evidence from prior literature on the bond markets, whereby bond investors also require higher premiums for split rated bonds than non-split rated bonds. This suggests that both ratings from Moody's and S&P are important for equity investors and that they consider both CRAs when assessing firms' credit risk. In addition, equity investors differentiate between split rated firms holding superior Moody's ratings and those with superior S&P ratings. Split rated firms with superior Moody's ratings have a higher cost of equity than their non-split rated peers, suggesting that equity investors put more weight on S&P, a more generous CRA, than Moody's, a more conservative CRA, when assessing firms' cost of equity capital. The results contrast with evidence from the bond market where bond investors place more emphasis on Moody's ratings. The potential reason for this is the different nature between equity investors and bond investors, whereas equity investors are firms' owners while bond investors are firms' creditors. In addition, our sample period differs from those of the earlier related papers on the cost of debt capital.

Chapter 4 considers the second research question: 'What is the impact of split ratings on firms' debt maturity decisions?'. A dataset of 884 U.S. corporations rated by Moody's and S&P during the period from 2003 to 2015 is considered. The debt maturity is calculated as the ratio of long-term debt (debt maturing in more than 3 or in more than 5 years) over the total debt. Chapter 4 hypothesizes that split ratings could play an important role in firms' debt maturity structure decisions. On the one hand, firms would want to issue more short-term debt to avoid the higher borrowing cost arising from split ratings as well as to signal their financial strength and reduce information asymmetry problems. On the other hand, the risk of an inability to roll-over maturing debt could induce split rated firms to issue more long-term debt. Hence, there are competing hypotheses to underpin the empirical analysis.

The results of Chapter 4 suggest that split rated firms on average have higher debt maturity ratios than non-split rated firms, suggesting that firms rely more on long-term debt when faced with CRAs' disagreement upon their creditworthiness. Firms with higher short-term debt are more likely to be downgraded and be subject to a higher cost of debt. Thus, split rated firms, who are characterised by greater information asymmetry, would want to rely more on long-term debt to avoid these threats. The results are most evident for larger firms and for firms with speculative-grade ratings. The results suggest that when facing the trade-off between issuing short-term debt to avoid the immediate higher cost of debt arising from split ratings and issuing long-term debt to avoid future potential higher roll-over risk, firms' managers choose the latter. Additionally, Chapter 4 finds that split rated firms with superior Moody's ratings tend to have a lower debt maturity ratio than those with superior S&P ratings. This suggests that firms with inferior Moody's ratings are more likely to have negative private information and more thereby be more concerned about potential future negative rating downgrades. This also suggests that firms' managers put different weight on Moody's ratings than S&P ratings when considering the optimal debt maturity structure. This result is consistent with some prior evidence from both the bond and equity markets, whereby both bond and equity investors place more emphasis on one CRA than the other. The results of Chapter 4 further confirm that both CRAs, Moody's and S&P, provide incremental important information to the market, especially to firms' managers.

Chapter 5 addresses the third research questions: 'What is the impact of split ratings on firms' capital structure decisions?'. A sample of 888 U.S. corporations rated by both Moody's and S&P from 2003 to 2015 is employed. Various capital structure definitions are included in different estimations. Because capital structure variables are applied as proportional dependent variables, the Tobit and GLM models are estimated to address the limitation of OLS estimation with regard to limited dependent variables. This Chapter is underpinned by three capital structure theories, namely, the trade-off theory, the pecking order theory and the market timing theory. According to the trade-off theory, firms are more likely to rely on short-term debt when facing a higher cost of borrowing as they trade-off the tax-shield benefit of long-term debt with the risk of bankruptcy. Thus, under the trade-off theory, split rated firms, who have higher long-term borrowing costs, are more likely to issue debt at the short end of the spectrum and have lower debt ratio compared to their non-split rated peers. In contrast, the pecking order theory suggests that firms' optimal capital structure decisions rely on the level of adverse selection relating to the sources of funds. Firms rely more on the financing source that has less adverse selection problem such as retained earnings and debt. In addition, firms with a substantial information asymmetry problem rely more on debt than equity. Thus, under the pecking order theory, split rated firms are more likely to use debt financing than equity financing compared to non-split rated firms. The market timing theory suggests that firms' optimal capital structure depends on prevailing conditions in both debt and equity markets. Firms raise funds on the more favourable market. Chapter 3 suggests that the magnitude of increased cost of equity capital arising from split ratings is higher than the cost of debt counterpart and therefore, for split rated firms, the debt market is more likely to be a more favourable market than the equity market. Thus, under the market timing theory, split rated firms may be expected to opt to issue more debt than their non-split rated peers.

Chapter 5 reveals that split rated firms on average have a higher optimal level of debt over total assets than non-split rated firms. The results are most evident for larger firms, and those with investment-grade ratings. Thus, the results of Chapter 5 show evidence supporting the pecking order and market timing theories. CRAs' disagreement about firms' creditworthiness signals the information opacity/ information asymmetry problem between firms and investors. Therefore, in order to mitigate these problems, firms with split ratings are more likely to issue more debt than equity. The results also suggest that split rated firms place more emphasis on the information asymmetry problem (adverse selection problem) than the increased borrowing cost arising from split ratings. In addition, the results of Chapter 5 show that the effect of superior Moody's ratings on capital structure is not significantly different from the case of superior S&P ratings. This suggests that firms' managers on average do not differentiate between Moody's and S&P when deciding upon optimal capital structure. This is in contrast with the evidence on how equity and bond investors react to split ratings and on how firms' managers decide the optimal debt maturity structure. This shows that firms' managers have different preferences with regard to credit ratings when considering the capital structure and debt maturity structure.

The thesis supports the argument that split ratings contribute new information to the market. Thus, one of principal implications for academic researchers and regulators is that they must recognise the differences between CRAs and should not treat them equally to each other. Regulators should examine why CRAs' ratings are different from each other and should question whether regulations are affected by these differences. If so, regulators must seek ways to differentiate CRAs within regulations.

The thesis provides a wide range of empirical implications for investors and corporations. For investors, split ratings are a symptom of firm opacity and can thereby be a signal of firms' holding negative private information about their creditworthiness (Livingston and Zhou, 2010; Goyal and Wang, 2013). Thus, investors could adjust their assessment of firms' cost of capital accordingly when split ratings prevail and persist. Therefore, equity investors can potentially discipline firms when they promptly impound the asymmetry information problem in the firms' security prices (i.e. increase required returns) and, by doing so, further affect the firms' financial decisions. Since the thesis provides evidence that split ratings are a key factor influencing investors' behaviour with regard to the cost of equity capital, potential future research could extend it to consider other aspects of investors' behaviour such as portfolio management.

One implication of the thesis for corporations is that firms' managers can take advantage of the information brought about by CRAs' disagreement about firms' creditworthiness. The thesis suggests that information asymmetry arising from split ratings can have a significant impact on firms' cost of capital (both equity and debt) as well as on the probability of firms experiencing future rating downgrades. Thus, firms would benefit substantially from improving their information producing process. High-quality accounting standards should be maintained in order to reduce information asymmetry/information opacity problems (Sengupta, 1998; Yu, 2005). In addition, firms could adjust their capital structure and debt maturity policies to address the potential for future financial constraints (rating deteriorations) typically coinciding with split ratings. In such situations, firms could use more bank financing than public debt or equity because it is a more flexible source of finance and firms with high proportion of bank financing are less sensitive to credit rating downgrades (Bendendo and Siming, 2018). Thus, another avenue for future research is to investigate the impact of CRAs' disagreement about firms' creditworthiness on firms' debt structure (different types of debt financing, i.e., bank loans, private debt or public debt financing). Future research could also investigate the impact of split ratings on firms' other financial behaviours, such as investment decisions and equity issuance decisions.

This thesis limits itself to examining the U.S., while little is known about the impact of split ratings on corporates in other countries. This can be constrained by the extent of usage of credit ratings, which will be less prominent than in the U.S. Nevertheless, further research on European and Asian countries could investigate whether the effect of split ratings on the equity market and on corporations' behaviour regarding debt maturity and capital structure differs across the globe.

In addition, one limitation of the thesis is an issue with the relative timing of rating actions. In some instances, CRAs' disagreement could be simply an outcome of one CRA being slower than the other CRA in adjusting its ratings. For example, one CRA issues an action and the other CRA might react and follow the same action, but at a much later date. This could lead to a short-term split rating between the two CRAs. However, this disagreement does not arise from any difference in fundamentals, but rather from a timing mismatch between rating transitions. Thus, to avoid this, split ratings in each of the empirical chapters are measured in such way as to mitigate the worst outcomes of this issue (i.e. split ratings are rounded to remove the impact of any short-term split). Timing issues arising from an event-related rating action would be a matter of weeks apart (at a maximum) not several months. Thus, the split rating measures employed in the thesis do not suffer from any large bias.

Another timing issue that may potentially affect the empirical analysis is that all of the variables used in the thesis are measured using balance sheet values and inevitably reflect decisions taken by the firms' managers in the past, not the present. This is due to the fact that the balance sheet reflects a situation prior to the observed split ratings. Both of these timing issues could be avoided by employing a sample of new issues (bond or equity), and this is an avenue that future research can usefully explore. However, there are inevitably both advantages and disadvantages of these two possible approaches and there are trade-offs involved in using new issues data.

Another limitation is that the thesis considers only rating disagreements relating to the two major CRAs, Moody's and S&P, whereas there are ten recognised CRAs (NRSROs) in the U.S. and Fitch is also a major CRAs. Thus, inclusion of another CRAs, especially Fitch, could reveal a richer dynamic relationship between CRAs and a more complete picture of split ratings' impact on the market and firms' behaviour. An additional area of interest is whether the market and firms respond differently to split ratings among CRAs with different business models, i.e. the issuer-pay model or investor-pay model.

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