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Ratings and Debt: an Analysis of the Link Between Credit Ratings and Capital Structure

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Abstract

In this paper we analyse the link between companies' credit ratings and their capital structure. We aim to determine whether prevailing company level credit ratings affect net issuance of debt. We construct a sample from Northern European countries which consists of 7,848 firm-years from 1990 to 2018. With OLS and time fixed effects frameworks, we analyse if companies close to a rating upgrade or downgrade issue less debt to facilitate a desirable rating outcome. We perform this analysis using both broad ratings (i.e. AA, A, A) and micro ratings (i.e. AA+, AA, AA-) and find statistically and economically significant results that indicate that, in both cases, proximity to a rating change leads to lower net issuance of debt. Our analysis of upgrade and downgrade effects in isolation shows that the upgrade effect is more evident in the broad ratings while the downgrade effect is more evident in the micro ratings.

Keywords: Credit Ratings, Capital Structure, Debt

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1. Introduction

Credit ratings have aided operation in financial markets for close to two hundred years. They provide investors with indispensable knowledge but are also often identified as culprits in financial crises. With each such financial crisis that has passed, they have continuously been questioned by media outlets and researchers alike. They especially highlight the role of Credit Rating Agencies (CRAs) in the recent 2008 financial crisis. Thus, Credit ratings are in the public's eye.

The Financial Times write (2019) "Some say the question marks over ratings could hinder foreign flows in to China's $12.5tn bond market," which provides a quick gauge of how integral credit ratings are to modern financial markets, the scepticism with which markets view them, and the sheer capital volumes that are in question. "Stating the obvious has been the foundation of rating agencies' business model for years, and they are doing well on it." the Financial Times (2019) write in an opinion editorial, referring to the many times CRAs have been so late to downgrade companies' debt that investors already faced the worst possible outcome. And indeed, the sector has been in the regulators' sight after the 2008 crisis and attempts have been made to break up the oligopoly type structure of the market.

Nevertheless, credit ratings serve a major function in financial markets. Rating changes are consistently covered by major news outlets and their effects are widespread: they drive asset prices (Goh & Ederington, 1999), they regulate what financial assets many large institutions may invest in (Ellul et al., 2011), serve as a mechanism for coordination between investors and companies (Boot et al., 2006), and investors rely on them in investment decisions (Adelino, 2009). Also, a company's credit rating affects its cost of capital (Kisgen, 2009), which is especially pronounced at the threshold for investment grade. Thus, companies have strong incentive to monitor their rating.

Correspondingly, dating back to the 1950's, the capital structure of companies has been richly researched. Most notably by Miller & Modigliani (1958), who laid the foundation for modern capital structure research and laid the foundation for the Pecking Order and Trade-off theories (Myers, 2001).

Some researchers try to combine the credit rating and capital structure research fields. Among them, Kisgen (2006, 2009 & 2010) investigates companies' capital structure strategy with regards to credit rating, and Bereskin et al. (2015) show that credit rating monitoring can have beneficial effects on corporate governance.

With this paper, we aspire to provide a further bridge between the two fields. While both fields are heavily researched, the connection between the two deserves more attention. We aim to expand on Kisgen's (2006) work, provide an update and broaden it outside of North America. We will also investigate if the link established by Kisgen (2006) exists beyond 2001.

With this research, firstly, we hope to provide guidance for regulators that preside over ratings regulation, including both national and international bodies. Secondly, our research may be useful for companies that face capital structure decisions. Thirdly, we believe this research to be beneficial or investors that rely on credit ratings in investment decisions, and, ultimately thereby contribute to better functioning financial markets.

We research this through collection and comparison of companies' issuance of debt and contrast it with the companies' proximity to a credit rating change. To investigate how debt issuance behaviour is affected by credit rating implications, we conduct OLS regressions on panel data (yearly observations) and observe differences in capital structure decisions based on proximity to a rating change. Proximity to a credit rating change is measured in two ways. Firstly, in terms of change from a broad ratings category (e.g. B to BB) and secondly, by micro ratings category (e.g. B to B+) through the construct of a credit score that we create, using common determinants of credit ratings and then ranking companies according to this score within each micro rating. Additionally, as one focus of this paper is to broaden the geographical scope of research that has been initiated on U.S data, we encompass a different region into our sample. Furthermore, in reference to how credit ratings guide investors, we look especially close at companies just above and below investment grade level.

The thesis is structured in the following way: After the introduction in Section 1, Section 2 provides a theoretical overview of the fields of both capital structure and credit ratings research and culminates in the deducted hypotheses of the thesis. Section 3 outlines the data used to perform our tests, how it was attained, and the considerations made in obtaining it. In Section 4, we detail our methodological approach, mainly OLS regressions on panel data. Section 5 presents the main results of our tests. In Section 6 we discuss the implications of the results, outline their limitations, and provide suggestions and guidelines for further research. Section 7 provides our conclusion, Section 8 contains the references, and Section 9 constitutes the appendices.

2. Literature Review

2.1 Capital Structure

Albeit the question of how companies are financed is older still, the origins of modern capital structure theories can be attributed to Miller and Modigliani (1958). They developed a theory that postulates that given perfect, frictionless market conditions with rational investors and full informational efficiency, the capital structure should be irrelevant. This theory served as a benchmark for most of the subsequent research and is the basis of most other capital structure theories, most notable of which are Trade-off and Pecking order theories (Myers, 2001). This subsection reviews these theories and other common explanations of optimal leverage and capital structure.

2.1.1 Trade-off Theory

According to the trade-off theory, a company will try to attain an optimal leverage ratio by maximizing the present value of the perpetual tax-shield minus the present value of financial distress. Hence, it is called the trade-off theory as it is a trade-off between leverage benefits in the form of tax shields and disadvantages in a form of increased risk of default and bankruptcy (Miller, 1977; Myers, 2001).

In addition to the theoretical framework, several authors have found empirical support for the trade-off theory. Frank and Goyal (2009) find that industry leverage, firm size, tangibility of assets, and market to book ratios are significant determinants of capital structure, which they directly link to the trade-off theory models. Furthermore, Leland (1994) estimates optimal leverage for a sample of firms, using factors such as taxes, risk, type of debt, and bankruptcy probability, and compares it with prevailing capital structures. He finds that companies indeed tend to have close to estimated target capital structures, which validates the trade-off theory. Hodder and Senbet (1990) replicate the key findings of Miller's (1977), accounting for differences in taxation, inflation, and exchange rates and show that the trade-off theory stays robust in an international setting.

Contrastingly, Myers (1984) and Shyam-Sunder and Myers (1999) argue that trade-off theory lacks empirical support and cannot explain debt preference over equity or market timing behaviour. In addition, Hennessy and Whited (2005) argue that the trade-off theory cannot explain differences in leverage for each individual investment and investment-based capital structure decision making. Overall, despite a very strong theoretical background, the trade-off theory has been difficult to fully prove empirically, and many caveats have been identified over the years.

2.1.2 Pecking Order Theory

Stewart C. Myers, a notable critic of the trade-off theory, combines some of the anomalies and limitations of the theory and proposes a pecking order theory of capital structure (Myers and Majluf, 1984). According to this theory, companies will choose to finance their investments at the lowest cost of capital, which means that the priority is given to internal over external funds and to debt over equity, and that the capital structure will reflect the need for capital for potential investments (Myers, 2001).

Overall, there is more empirical support for the pecking order theory than there is for the traditional trade-off theory. Myers (1984), and Shyam-Sunder Myers (1999), argue that the existing evidence is in favour of the pecking order theory. However, Frank and Goyal (2003) find in their research of companies from the 1970s to the 1990s, that large companies behave according to the pecking order theory in the early part of their sample, but the evidence is weaker when analysing smaller firms, and periods past the 1989. Furthermore, both the trade-off and the pecking order theories implicitly assume that managers act in the best interest of shareholders, which may not be the case. However, Myers (1984) argues that it is always possible to find anomalies which have no impact on a company's value, and calls these anomalies "neutral mutations", meaning that they have no positive or negative effect and thus are allowed to persist.

2.1.3 Other common observations and theories

In addition to the traditional theories, there are many other explanations of capital structure which aim to address the drawbacks of these theories. These explanations are related to agency costs, information asymmetry, and other factors.

One of the common criticisms towards the traditional capital structure theories is the assumption of no agency costs (Harris and Raviv, 1991). Harris and Raviv (1990) argue that managers do not act in the best interests of shareholders, but that debt serves as a disciplinary measure to reduce the agency costs. Similarly, Berger, Ofek, and Yermack (2012) note that entrenched CEOs with long tenures tend to underlever the companies as it reduces volatility and risk of default, which in turn reduces their risk of replacement. Furthermore, the free cash flow theory states that firms which have excess cash flow from operations, compared to capital expenditure needs, will tend to overinvest. Therefore, debt can be beneficial even when the costs of financial distress are high due to its disciplinary effect (Myers, 2001).

Furthermore, information asymmetry is one of the other commonly analysed factors considered in debt issuance. Market timing, when issuing debt, serves as evidence for the informational asymmetry: companies tend to use debt financing when their valuations are low, and issue equity when their valuations are high, in this way benefiting the old shareholders at the cost of new ones (Myers, 1984; Harris and Raviv, 1991; Rixtel, González, Yang, 2015). Hovakimian et al. (2004) even argue that, although companies may have a target leverage ratio, constant efforts to time the market prevent them from reaching the target. As a result, Baker and Wurgler (2002) conclude that the prevailing capital structure is a consequence of all past attempts to time the market with respect to equity issuance and buybacks. Furthermore, Harris and Raviv (1990) argue that debt policies may be used to tackle this asymmetry and investors can push companies to take on more debt due to the company's information benefits: ability to make payments, and that banks' willingness to lend generates a positive signal. However, even though informational asymmetry may be considered as a separate factor that affects capital structure policies, it is partially linked with the pecking order theory. Differences in cost of capital across internal finance, equity and debt is a result of informational asymmetry between different investor groups (Myers and Majluf, 1984).

Moreover, other authors have developed additional theories by combining previous research. Fischer et al. (1989) determine that optimal leverage is time varying and dependent on individual firm characteristics that affect recapitalization costs. They find that market risk, credit risk, and firm size affect the extent of fluctuations in leverage. Contrastingly, Hennessy and Whited (2005) explain that constant swings and variation in capital structure are due to investment decision making processes within companies. Capital structure decisions are made on individual investment project basis based on prevailing financing margins and costs. Myers (1977) offers an alternative approach towards refinancing. He proposes that once established, stable assets are financed with collateralized debt while growth opportunities are more likely to be equity financed. Asset collateral value, market to book ratio, growth, and volatility effects have been further proven to impact capital structure by Titman and Wessels (1988) and Frank and Goyal (2009). Finally, Myers (2001) notes that none of the theories can fully explain capital structure and there is a constant need of new research in the field. Zingales (2000), acknowledges this claim and notes that companies are constantly changing and there has been a significant change from physical capital-intensive industrial firms of the 1970s to more human capital-based service companies of the present, which has significant implications on capital structure decisions.

2.2 Credit Ratings

2.2.1 Historical Overview

Primarily as a measure of creditworthiness of a security, credit ratings came to the public's eye on the eve of the financial crisis in 2007-2008, the issues that presented themselves in the aftermath of the crisis sparked a surge of new research in the field as well as regulatory attention. However, ratings have for long been omnipresent in financial markets and they have been utilized by investors as a quality gauge for close to 200 years (Cantor & Packer, 1994). The first rating institutes were Poor's (later merged to become Standard & Poor's) and Moody's. Together with their younger competitor Fitch, these players dominate the market, making up more than 90% of total market share (European Securities and Market Authority).

Traditionally, the US Credit market has been characterized by more direct lending, private placements and bond financing through capital markets whereas Europe has been dominated by bank lending (White, 2002). Therefore, the need for rating agencies arose first in the US and indeed these American players dominate the European market as well.

After the great depression of 1929, investor demand for ratings grew rapidly in fears of credit defaults. In 1931 they were first incorporated into official regulation when the U.S. treasury department adopted them as formal indication of bond account qualityIn 1975, the U.S. Securities and exchange Commission administered the designation Nationally Recognized Statistical Rating Organization (NRSRO) and mandated that credit rating agencies that held the title were to be used for fulfilling credit rating-dependent regulatory duties. The NRSRO designation is one of the reasons that the oligopoly-structure of the market is entrenched, as it raises barriers to entry (White, 2009). It is disputed whether the designation has led to higher ratings, i.e. ratings inflation. Fairchild et al. (2015) test whether the yields of bonds rated by a CRA before and after the CRA obtains an NRSRO designation to find that there is no change in yields, implying no inflation. However, Behr et al. (2018) test whether Moody's ratings differed in ability to predict defaults before and after the NRSRO designation and find supporting evidence for inflation. Furthermore, increased competition following regulators calls after the 2007-2008 financial crisis led to further incentive issues that resulted in ratings inflation, as shown by Becker & Milbourn (2011) who analyse the entry of Fitch as a third player in the credit rating market. Fulghieri et al. (2010) suggest CRAs instead issue unsolicited credit ratings to accommodate the incentives issue of issuer-pay ratings.

2.2.2 Credit Ratings Rationale

Banks may perform screening and monitoring of debt (Diamond, 1984), however, in a market where banks play a smaller part, CRAs may instead fill this role. As such, CRAs serve to reduce transaction costs. The information asymmetry that exists naturally between lender and borrower can be alleviated by this third-party monitoring, without the rated entity needing to divulge any sensitive information that may aid their competition (White, 2002).

Choi (1997) argues that the CRAs have an incentive to perform diligent monitoring as they must preserve their reputation. However, he identifies CRAs lack of liability as an issue and does not rule out regulation where the reputation model does not yield satisfactory result. Additionally, the reputation mechanism may work poorly, especially in the case of novel financial products, as was displayed with Mortgage Backed Securities (MBS) in the 2007-2008 financial crisis (Hunt, 2009, Bolton et al. 2009, Mathis et al., 2009). Furthermore, by examining default rates on the basis of initial ratings, Cornaggia et al. (2012; 2017) show that ratings may be inconsistent across asset classes and Bar & Shapiro (2013) show that ratings quality varies over the business cycle (ratings are counter-cyclical) due to fundamental economic factors as CRAs look to smoothen earnings.

Initially, investors paid the rating agencies for the rating. However, it changed in the 1970's when the companies started to pay for their own ratings. This change created potential agency issues and moral hazard as the companies were both customers and subjects of scrutiny for the CRAs and ratings inflation has indeed been observed (Partnoy, 2006, Griffin et al. 2013). Jian et al. (2013) compare ratings from S&P before and after the switch from investor-pay to issuer-pay ratings with Moody's as the benchmark and detect evidence of comparatively higher ratings.

Credit ratings as coordinating mechanism for firms and investors (Boot et al., 2006). Evidently, investors rely heavily on credit ratings, especially concerning complex financial assets where investors may not completely understand the asset (Adelino, 2009). Cuchra (2005) shows that credit rating is the largest explanatory factor for credit spreads at time of issuance. Subsequently, ratings affect asset prices in financial markets. (Hand et al., 1992). Withal, beyond the primary negative price effect of a rating downgrade, there is a continued economic effect on companies as a rating downgrade can trigger further deterioration as markets lose confidence in the company. Manso (2013) argues that CRAs should accommodate this issue within their ratings.

Additionally, ratings influence investments as some institutional investors face restraints as to what they may invest in with regards to rating (Cantor & Packer 1997; Ellul et al. 2011) which can lead to distortions in prices due to fire-sales, especially in the case of a downgrade from investment-grade to non-investment-grade, as shown by Ellul et al. (2011) who looks at transaction data from insurance companies in case of ratings downgrade to junk. Furthermore, the market views the rating as a gauge of asset quality and while Weinstein (1977) finds that asset price does not suffer negatively after a rating downgrade, there is a subsequent overwhelming amount of papers that stipulate the opposite (Hand et al. 1992; Goh and Ederington, 1993; 1999; Cornell et al. 1989; Steiner and Heinke, 2001; Chen et al., 2012).

2.2.3 Credit Ratings and Strategy

With the weight credit ratings carry in financial markets, companies do well to account for their credit rating. And indeed, research shows that they change their operational strategy to do so. Measures include reduction of Research and Development and Selling, General & Administrative Expenses to meet key ratios commonly used by rating institutes such as Debt/EBITDA (Begley, 2014). Furthermore, that they adjust capital structure to influence their credit rating, as shown by Kisgen (2009) who analyses company behaviour after a rating downgrade and find that they issue less debt. Going further, Alissa et al. (2013) show that there is evidence of earnings management to align with ratings by constructing a measure for an “expected rating”, compare it to the companies’ actual rating and evaluate if there is a difference in level earnings management between companies whose rating is aligned, and companies whose rating is not. Bereskin et al. (2015) show that this applies most strongly to companies that rely on external financing more heavily on a Korean sample. Lastly, Kisgen and Strahan (2010) use the SEC’s certification of another CRA to show that companies’ cost of capital depends on credit rating regulation.

Furthermore, companies can influence their rating as the structure where companies pay for their own ratings allows for “ratings shopping”. This refers to when a company contacts different rating agencies and only publishes the best rating received, as shown by Griffin et al. (2013) who compare the performance of securities with one rating to securities with multiple ratings. Likewise, companies can use competition among CRAs which makes CRAs cater to the rated companies (Bolton et al., 2012). Kraft (2014) further adds to the literature on CRAs catering by comparing the ratings of companies with loan contracts that depend on rating with control companies. He finds that shocks are less visible in the ratings of those with loan contracts dependent on ratings. In conclusion, there is mounting evidence of the bilateral nature of the relationship between CRAs and rated companies that we aspire to expound on.

2.3 Hypotheses Specification

Credit ratings and capital structure are related via a number of channels. Firstly, the usage of credit ratings to address informational asymmetry and provide credit information to investors addresses an underlying foundation for the pecking order theory. Furthermore, credit ratings account for several factors that affects capital structure such as bankruptcy risk, growth potential, outstanding leverage level, risk or volatility, and therefore directly affect access to financing and its costs. Furthermore, it has been heavily demonstrated that investors rely on credit ratings and that ratings drive asset prices (Hand et al. 1992; Goh and Ederington, 1993). Investors sentiment in turn dictates cost of capital and cost of capital is crucial to all companies. Thus, it follows that credit ratings are important to companies and affect their operations and strategy. Companies dispose over several tools to influence their rating and have incentives to do it. Therefore, research on the subject is merited.

Credit ratings are fundamentally an evaluation of the risk of a financial asset. Leverage, in turn, is a key driver of risk in financial assets. Therefore, it is implicit that credit ratings are critical to capital structure and debt decision making. However, so far there has been limited research done in this field. Kisgen (2006), analyses a set of publicly traded US companies from 1986 to 2001 and finds that credit ratings play a significant role in issuance of debt. We intend to further this research from two perspectives by analysing the companies outside of the US, and by focusing on the years preceding and following the Great Recession of 2008-2009, which has had a significant impact on the credit ratings and the issuing agencies (Pagano et al. 2010).

We hypothesise that companies close to a rating upgrade or downgrade will tend to issue less debt in hopes to attain this upgrade or avoid the downgrade. We test this pattern in two ways: Firstly, if a company near a broad rating change (letter coded credit ratings, such as AA, BBB, C) issues less debt. Secondly, there are more frequent intermittent ratings changes within each broad rating. We define these as micro ratings changes. Micro ratings are coded as plus, minus, or neutral, such as AA+, AA, and AA. Following the methodology of Kisgen (2006), we hypothesise that the "best" and the "worst" companies within each micro rating also issue less debt than their peers in order to facilitate a beneficial ratings treatment.

Thus, we narrow down the following research questions and hypotheses:

Main RQ: Do companies close to a rating change issue less debt than the others?

1. Do companies close to a broad rating upgrade or downgrade issue less debt?
    a. H1: Companies that have plus, or minus ratings issue less debt than neutral
    b. H2: Companies that have plus rating issue less debt than neutral
    c. H3: Companies that have minus rating issue less debt than neutral
2. Do companies close to a micro rating upgrade or downgrade issue less debt?
    a. H4: Companies above the top or below the bottom threshold of micro rating issue less debt
    b. H5: Companies above the top threshold of micro rating issue less debt
    c. H6: Companies below the bottom threshold of micro rating issue less debt

If so, it would prove that companies adjust their debt issuance and capital structure to optimize their credit rating. Detailed estimations of each of the parameters are presented in the following sections.

3. Data

This section provides an overview on the considerations of the data selection, sources, the data used to construct the main variables, the credit score and the subsequent cleaning process.

3.1 Overview

We focus our research on the northern European region, which by our definition includes Iceland, Norway, Sweden, Finland, Estonia, Latvia, Lithuania, Denmark, Germany, the Netherlands, the United Kingdom and Ireland[1]. This selection is done due to their geographic proximity, as well as economic and financial integration (Albulescu, 2017).

Thomson Reuters Eikon serves as our main data source, which we use to access annual balance sheet, income statement and credit rating data. We also cross-check key variables with publicly available annual report and credit rating data. Our sample period lasts from 1990 to 2018, which includes several business and financial cycles, however data is sparser in the earlier years as illustrated in Figure 3.1. There are notably less observations in 2018 because not all annual reports for this year were available to us during the data gathering process.

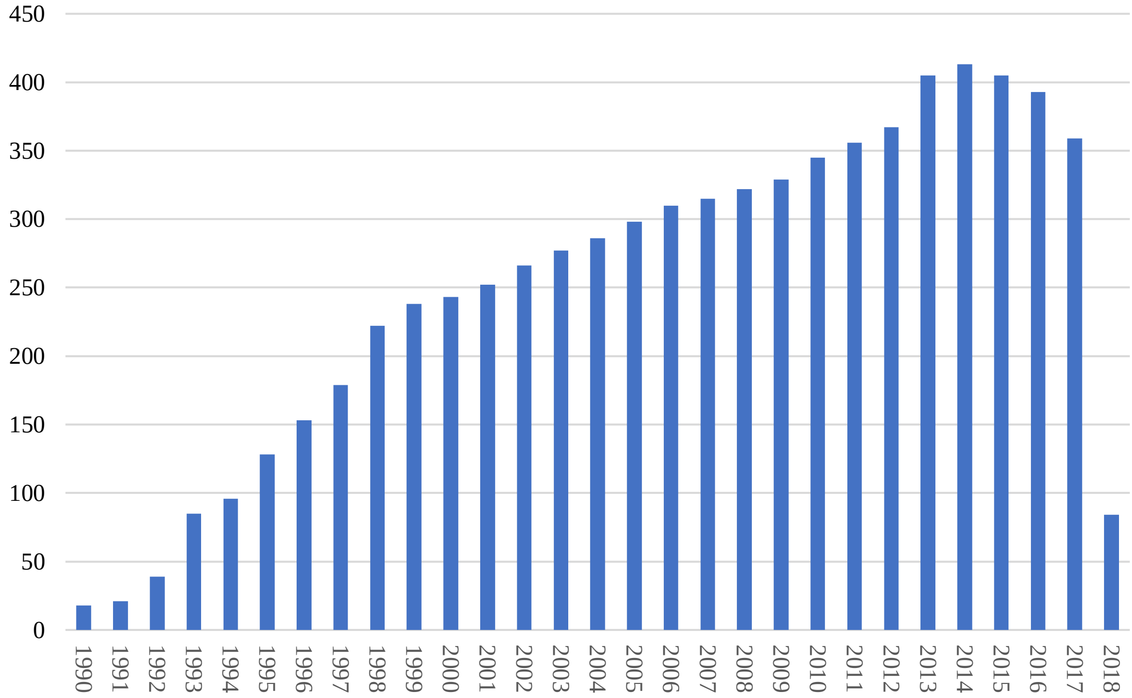

Figure 3.1. Number of firm-year observations across years

[1] We note that the final sample after cleaning processes included no observations in Estonia or Latvia.

We collect annual balance sheet, income statement data as well as general information of publicly listed companies in the chosen countries and over the indicated period from 1990 to 2018. A list of data items is presented below in Table 3.1.

Balance Sheet	**Income Statement**	**General**
Total Debt	Revenue	Reuters Instrument Code (RIC)
Total Equity	EBITDA	International Securities
Total Assets	EBIT	Identification Number (ISIN)
Net Issuance and Retirement of Stock (Cumulative)	Interest Expense	Thomson Reuters Industry Classification
Net Issuance and Retirement of Debt (Cumulative)	Net Income	S&P long term outlook rating (Domestic and Foreign)
Market Capitalization		
Currency (Reporting and Traded)		

Table 3.1. Collected data items

This information is required to identify the companies in our sample and to obtain key variables to be used in the main analysis and subsequent robustness checks. As the main aim is to test the relationship between the ratings and debt issuance, debt issuance and credit ratings are the key variables required. To obtain the net debt issuance variable, we subtract equity issuance from debt issuance and divide the obtain results by total assets. Regarding the ratings variable, in line with Kisgen (2006), we choose S&P long term outlook rating as our ratings variable since it encompasses information about the whole firm and does not isolate individual bonds or debt instruments. We use long-term ratings as companies typically have long-term capital structure strategies with debt issuances that have maturities stretching beyond one year (Kisgen, 2009). We treat all years between a change of rating as an observation with the last issued rating. Both domestic and foreign ratings are available but in our main analysis we use domestic rating while the foreign rating is kept for robustness checks. However, domestic and foreign ratings highly overlap.

We base our main research on the restated balance sheets as this information is more reliable, especially when considering earlier years. However, the original balance sheets are used in the robustness checks and therefore all balance sheets items are obtained using both restated and original information. In addition, we use book values in the main analysis as it is in line with Kisgen (2006) as well as Standard and Poor’s Standard (2011), which is used to allocate the ratings to companies. However, market values are also obtained and used in the robustness checks. Information such as balance sheet and stock trading currencies as well as

RIC, ISIN codes, and industry classification is required for data matching and sector-based analysis.

Considering other inputs, income statement data is used to obtain control variables as well as variables required to compute credit scores which are used to determine the thresholds for grouping of companies within the micro ratings. To account for differences in leverage levels, company size and profitability, we add respective control variables. *Leverage* is denoted as debt over total capital, *size* is estimated using sales data while *profitability* is accounted for by EBITDA over total assets in line with Kisgen (2006). These variables as well as other income data items such as EBIT and Net Income are also required for the calculations of the credit scores as they are key drivers of credit ratings (Standard and Poor's, 2011).

3.2 Data cleaning and Main Sample

Once collected, our initial data sample before the cleaning process includes 7,848 firm-year observations of 26 variables, 444 firms and 174,088 individual data points. As part of our data matching process, we move all observations to the beginning of the year if they are recorded until June 30th of the given year while observations from July 1st onwards are moved to the end of year. In cases where there is more than one observation per year, this data matching method creates duplicate panel data variables, which are eliminated in the first stage of data cleaning process. Furthermore, we use RIC and ISIN matching to eliminate duplicates, cross-listed firms as well as exchange traded certificates, such as bull and bear certificates on company stock. This step results in 6,701 firm-year observations of 363 firms and 150,758 individual data points and is noted as our Panel A. Furthermore, we exclude large debt offerings that exceed 10% of total assets because it is almost certain that such high issuance of debt will result in a rating change and companies undergo such action as a part of larger capital restructuring process. This methodology follows Kisgen (2006) who also excludes observations where such issuances occur. The obtained data sample is denoted as Panel B and includes 6,160 firm-years, 354 companies, and 126,770 individual data points. Finally, we also exclude large equity offerings that exceed 10% of total assets and obtain our final sample of 6,003 firm-years, 329 companies and 93,235 individual data points, which we denote as Main Panel. The data cleaning process is summarised in Table 3.2.

Process	Panel	Firms	Firm-years	Individual data points
Initial Data	-	444	7,848	174,088
Eliminating observations with same date and firm	-	443	7,772	173,248
Eliminating duplicates, cross listed firms and non-equity instruments	A	363	6,701	150,758
Eliminating debt offerings > 10% of assets	B	354	6,160	126,770
Eliminating equity offerings > 10% of assets	Main Panel	329	6,003	93,235

Table 3.2. Summary of the cleaning process.

We do all subsequent analysis using the Main Panel with 6,003 firm-years. However, we also report the main regression results using Panel A and Panel B in the appendices as it ensures increased comparability between our and Kisgen's (2006) findings, who reports findings across different data-cleaning methods. It is also noteworthy that even though final sample includes 6,003 firm-years, we also exclude observations where required data items are missing, which depends on the specific regression chosen. Therefore, each model used in our analysis has slightly different number of active observations.

Micro Rating	Observations	Broad Rating	Observations
AAA	11	AAA	11
AA+	32	AA	236
AA	62	A	727
AA-	142	BBB	891
A+	207	BB	285
A	215	B	147
A-	305	CCC	5
BBB+	400	CC	4
BBB	303	D	1
BBB-	188		
BB+	120		
BB	101		
BB-	64		
B+	60		
B	61		
B-	26		
CCC+	3		
CCC-	2		
CC	4		
D	1		

Table 3.3. Number of observations across micro and broad ratings.

Table 3.3 presents how Main Panel observations are split across ratings. Although, there are observations across most rating categories, the split is not even, and the majority of observations are concentrated at A and BBB broad ratings. However, the micro ratings within each broad rating are split rather evenly with slightly more minus rated firms in A and AA ratings and slightly more plus rated firms in BBB, BB, and B ratings. Furthermore, Figure 3.3 illustrates how the average net issuance of debt is split across the ratings. Lower rated firms, on average, reduce their leverage while the higher rated companies of our sample have positive debt issuance balances. This pattern illustrates the importance of control variables as other factors than the rating, are clearly affecting the issuance of debt.

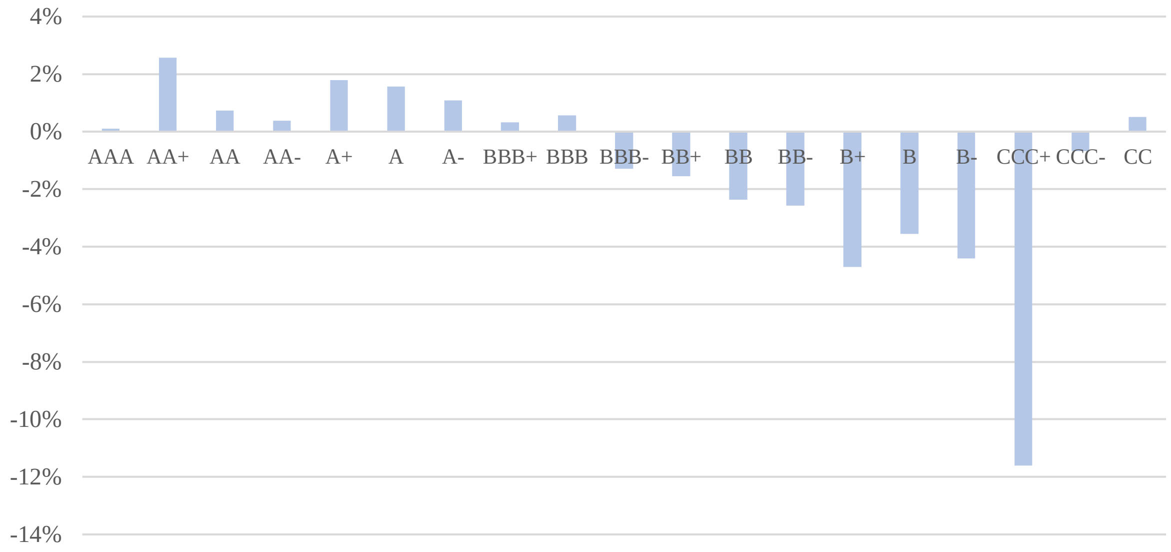

Figure 3.2. Collected observations of average Net Debt Issued across ratings.

4. Methodology

In order to answer the abovementioned research questions, and test the hypotheses, we use methodology applied from Kisgen (2006), as it is one of the most comprehensive studies done in this field which analyses ratings and capital structure. As described above, we approach the research questions by dividing ratings into two groups: broad (i.e. AA, A, A), and micro (i.e. AA+, AA, AA-) and use pooled OLS regression method. In addition, we enhance the model by introducing interaction terms as well as by accounting for potential statistical biases using a fixed effects regression model.

4.1 Broad Ratings

To test hypotheses H1-H3; whether the companies that have plus or minus rating issue less debt than the neutrally rated companies, we develop the broad ratings test. We define the following effects: *Plus or minus* (POM), *Plus*, and *Minus*, which respectively refer to hypotheses H1, H2 and H3. We run pooled OLS regressions using the panel data of required variables across firms and years. We choose this method instead of time series design as we do not expect the importance of credit ratings in capital structure decision making to vary during our analysis period. We revisit this assumption in subsection 4.4.

The dependent variable in our analysis is net issuance of debt, which is calculated as issuance of debt minus net issuance of equity over total assets. This facilitates comparability between companies of different size.

The independent variables consist of three dummy and three control variables (as outlined in the data section), which are used in line with Kisgen (2006) to account for other determinants of debt issuance. We use the following regressions:

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPOM_{t,f} + \varepsilon_{t,f} \quad (1)$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPOM_{t,f} + \beta_2 Leverage_{t,f} + \beta_2 Profitability_{t,f} + \beta_3 lnSales_{t,f} + \varepsilon_{t,f} \quad (2)$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPlus_{t,f} + \beta_2 CRMinus_{t,f} + \varepsilon_{t,f} \quad (3)$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPlus_{t,f} + \beta_2 CRMinus_{t,f} + \beta_3 Leverage_{t,f} + \beta_4 Profitability_{t,f} + \beta_5 lnSales_{t,f} + \varepsilon_{t,f} \quad (4)$$

where,

$NetDI_{t,f}$ – is the net issuance of debt with respect to total assets across all companies and years

$CRPOM_{t,f}$ – is the dummy variable for companies and periods where the current credit rating is either + or –

$CRPlus_{t,f}$ – is the dummy variable for companies and periods where the current credit rating is +

$CRMinus_{t,f}$ – is the dummy variable for companies and periods where the current credit rating is -

$Leverage_{t,f}$ – is the control variable equal to book value of debt over total capital at t = t – 1

$Profitability_{t,f}$ – is the control variable equal to EBITDA over total assets at t = t – 1

$lnSales_{t,f}$ is the control variable equal to natural logarithm of net sales at t = t – 1

Regressions (1) and (2) are used to test hypothesis H1, while regressions (3), and (4) are used to test hypotheses H2, and H3.

4.2 Micro Ratings

We develop the micro rating regressions to test hypotheses H4-H6, whether companies that are within the top or bottom group of the micro rating issue less debt than the companies in the middle group. Similarly, as in the broad rating case, we analyse whether proximity to a micro rating upgrade or downgrade leads to lower debt issuance. We define the following effects: *High or low* (HOL), *High*, and *Low*, which respectively refer to hypotheses H4, H5 and H6. However, in this case, unlike the broad ratings, micro ratings have no readily available indicators, such as plus or minus. Therefore, we construct a measure of proximity to a rating change (credit score) to rank companies within each micro rating category.

4.2.1 Credit Score Analysis

In line with Kisgen (2006), we divide companies within each micro rating into groups based on their credit score. The credit score is a derived measure of creditworthiness calculated based on the common determinants of credit ratings, as listed by Standard and Poor's (2011). We use 7 variables to predict the rating: net income over total assets, debt over total capital squared, EBITDA over interest expense, EBIT over interest expense, natural logarithm of total assets, and EBITDA with respect to assets. Similarly, these variables have been used by other researchers to analyse the credit ratings (Pogue & Soldofsky, 1969; Kaplan & Urwitz, 1979; Kamstra et al., 2001; Ederington, 1985; Kisgen, 2006). The expected relationship is that net income over assets, EBITDA and EBIT over interest expense, natural logarithm of assets, and EBITDA over assets will have a positive effect on the credit rating as better profitability, larger size, and creditworthiness of the company are all naturally related to better further outlook and lower probability of default. On the other hand, the combined effect of debt over total capital and debt over total capital squared is expected to be negative as it leads to higher risk of financial distress that negatively affects the given credit rating. Consequently, we obtain the following OLS regression:

$$Ranking_{t,f} = \beta_0 + \beta_1 \frac{Net\ Income_{t,f}}{Assets_{t,f}} + \beta_2 \frac{Debt_{t,f}}{Debt_{t,f}+Equity_{t,f}} + \beta_3 \left(\frac{Debt_{t,f}}{Debt_{t,f}+Equity_{t,f}}\right)^2 + \beta_4 \frac{EBITDA_{t,f}}{Interest\ Expense_{t,f}} + \beta_5 \frac{EBIT_{t,f}}{Interest\ Expense_{t,f}} + \beta_6 \ln\left(Assets_{t,f}\right) + \beta_7 \frac{EBITDA_{t,f}}{Assets_{t,f}} + \varepsilon_{t,f} \quad \text{(CS1)}$$

where,

$Ranking_{t,f}$ – is the micro rating ranking from 1 to 26, 1 representing D, and 26 representing AAA.

We then determine which coefficients are statistically and economically significant, re-run the regression and use the coefficients to calculate respective credit scores for each firm-year. Finally, based on these credit scores, we assign the top 25% companies as close to a micro rating upgrade in a given year, while the bottom 25% are assigned as close to a downgrade.

4.2.2 Micro Rating Regressions

Once the companies within each micro rating are divided into their respective groups, we apply the same four regression models as above to analyse the effect on debt issuance. Thus, the OLS regressions are:

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHOL_{t,f} + \varepsilon_{t,f} \quad (5)$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHOL_{t,f} + \beta_2 Leverage_{t,f} + \beta_3 Profitability_{t,f} + \beta_4 lnSales_{t,f} + \varepsilon_{t,f} \quad (6)$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHigh_{t,f} + \beta_2 CRLow_{t,f} + \varepsilon_{t,f} \quad (7)$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHigh_{t,f} + \beta_2 CRLow_{t,f} + \beta_3 Leverage_{t,f} + \beta_4 Profitability_{t,f} + \beta_5 lnSales_{t,f} + \varepsilon_{t,f} \quad (8)$$

where,

$CRHOL_{t,f}$ – the dummy variable for companies and periods where the micro rating credit score is in the highest or lowest 25%.

$CRHigh_{t,f}$ – the dummy variable for companies and periods where the micro rating credit score is in the highest 25%.

$CRLow_{t,f}$ – the dummy variable for companies and periods where the micro rating credit score is in the lowest 25%.

Regressions (5) and (6) are used to test hypothesis H4, while regressions (7), and (8) are used to test hypotheses H5, and H6.

4.3 Interaction Terms

In addition to the regressions adapted from Kisgen (2006), we also add interaction credit rating variables to analyse whether the effect of proximity to rating change is constant or whether it varies across ratings. For the purpose of this analysis, we use the previously obtained *Ranking* variable which assigns consecutive numbers to each rating from D to AAA and obtain the following regression forms:

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPOM_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRPOM{:}Ranking_{t,f} + \varepsilon_{t,f} \tag{1I}$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPOM_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRPOM{:}Ranking_{t,f} + C_{t,f} + \varepsilon_{t,f} \tag{2I}$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPlus_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRPlus{:}Ranking_{t,f} + \beta_4 CRMinus_{t,f} + \beta_5 CRMinus{:}Ranking_{t,f} + \varepsilon_{t,f} \tag{3I}$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRPlus_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRPlus{:}Ranking_{t,f} + \beta_4 CRMinus_{t,f} + \beta_5 CRMinus{:}Ranking_{t,f} + C_{t,f} + \varepsilon_{t,f} \tag{4I}$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHOL_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRHOL{:}Ranking_{t,f} + \varepsilon_{t,f} \tag{5I}$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHOL_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRHOL{:}Ranking_{t,f} + C_{t,f} + \varepsilon_{t,f} \tag{6I}$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHigh_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRHigh{:}Ranking_{t,f} + \beta_4 CRLow_{t,f} + \beta_5 CRLow{:}Ranking_{t,f} + \varepsilon_{t,f} \tag{7I}$$

$$NetDI_{t,f} = \beta_0 + \beta_1 CRHigh_{t,f} + \beta_2 Ranking_{t,f} + \beta_3 CRHigh{:}Ranking_{t,f} + \beta_4 CRLow_{t,f} + \beta_5 CRLow{:}Ranking_{t,f} + C_{t,f} + \varepsilon_{t,f} \tag{8I}$$

where,

$C_{t,f}$ – is the set of control variables: leverage, profitability, and lnSales.

$CRPOM{:}Ranking_{t,f}$ – is the interaction term between *CRPOM* and *Ranking* variable

$CRPlus{:}Ranking_{t,f}$ – is the interaction term between *CRPlus* and *Ranking* variable

$CRMinus{:}Ranking_{t,f}$ – is the interaction term between *CRMinus* and *Ranking* variable

$CRHOL{:}Ranking_{t,f}$ – is the interaction term between *CRHOL* and *Ranking* variable

$CRHigh{:}Ranking_{t,f}$ – is the interaction term between *CRHigh* and *Ranking* variable

$CRLow{:}Ranking_{t,f}$ – is the interaction term between *CRLow* and *Ranking* variable

4.4 Fixed Effects Model

The pooled OLS method builds on the underlying assumption that the effects are homogenous across years and firms. However, this homogeneity has not been established. Thus, to address this issue, we use Breusch-Pagan Lagrange Multiplier tests and a fixed effects model (Breusch & Pagan, 1980).

The Breusch-Pagan Lagrange Multiplier test is used to determine whether the intercept is different across a predefined individual effect. The null hypothesis is that the effect is zero and the rejection of it implies that the individual effect is significant. In our case, we use it to test for time fixed effects and consequently run regressions (1) – (8) using a time fixed effects setup with time-clustered standard errors. This method allows us to account for different effects across years. It is also reasonable from an economic perspective as our chosen control variables do not account for factors, such as debt capital availability, future outlook and investor sentiment, all of which are known to vary during different changes over the business cycle. Therefore, these effects can be partially captured in different effects across years.

4.5 Alternative Models

In addition to the fixed effects, an alternative method to account for time effects is to use a random effects model. A random effects model is an alternative method to demean the data similarly as in the fixed effects model but in this case, the intercept can be kept together with a time-invariant residual error. The underlying issue is that, in this case, we must assume that the time-invariant residual error is uncorrelated with the independent variables (Wooldridge, 2005). Therefore, we find it more prudent to use the fixed effects model instead.

Furthermore, another alternative is to analyse the opposite effect of how rating upgrades or downgrades depend on debt issuance. This analysis would be useful in testing whether the reasoning that fear of downgrade or hope for upgrade is rational (Kisgen, 2009; Molina, 2005). It could be done using logit and probit models where the dependent variable is probability of rating upgrade/downgrade and the independent variable is lagged net debt issuance. However, the lack of longitudinal data makes such a specification difficult as it requires observations of the same companies across time, but rating changes are relatively rare events. Therefore, we conclude that such analysis is not feasible in this case.

5. Results Description

This section summarises main regression results as defined in the methodology section in order to answer the main research question of whether the companies close to a rating change issue less debt. We conduct broad and micro rating regressions using pooled OLS and fixed effects models as well as test the robustness of the findings using alternative model specifications. We also link our obtained results to previous research, namely Kisgen (2006), whose models and findings are directly comparable with our analysis.

5.1 Broad Ratings Regressions

We start our analysis by focusing on the regressions using broad ratings and analyse whether companies that have plus or minus ratings tend to issue less debt than the companies with neutral ratings. Pooled OLS regression results based on regressions (1) – (4) are presented below in Table 5.1. The table illustrates the results using main data panel, as described in the Data section, where large equity and debt offerings are excluded. The results using alternative data cleaning methods are reported in Appendix 3.

	(1)	(2)	(3)	(4)
Intercept	0.001	-0.09***	0.001	-0.089***
	(0.534)	(0.000)	(0.534)	(0.000)
CRPOM	-0.002	-0.007**		
	(0.510)	(0.017)		
CRPlus			-0.0004	-0.007**
			(0.890)	(0.026)
CRMinus			-0.003	-0.006*
			(0.295)	(0.058)
Leverage		-0.035***		-0.035***
		(0.000)		(0.000)
Profitability		0.171***		0.171***
		(0.000)		(0.000)
lnSales		0.004***		0.004***
		(0.000)		(0.000)
Adj. R^2	-0.0002	0.094	-0.0003	0.093
Obs.	2,306	1,766	2,306	1,766

Table 5.1. Broad rating pooled OLS regression results using regressions (1) – (4)

We analyse the effect within the broad ratings using three variables. Firstly, *CRPOM* refers to the Plus or Minus (POM) effect, which measures the effect on net issuance of debt for companies that have plus or minus ratings. Then, we disentangle this effect and analyse the Plus and Minus effects in isolation using the *CRPlus* and *CRMinus* variables. The key output from these results are the POM, Plus and Minus coefficients and their p-values (statistical significance). The coefficient represents the effect of each rating category to the net issuance of debt when compared to the default (neutral) rating (i.e. A, AA, AAA). As expected, the Plus or Minus (POM) effect is negative in both regressions, with and without controls and the coefficients are -0.7pp and -0.2pp, respectively. According to these results, plus or minus rated companies issue 0.7pp and 0.2pp less net debt with respect to assets than the companies of neutral rating. The effect is stronger and more economically significant in regression (2) where the control variables: *Profitability*, *Leverage* and *lnSales* are accounted for.

Regressions (3) and (4) are used to analyse the Plus and Minus effects separately. This analysis provides additional information on whether the strength and statistical significance of these effects is balanced or whether some effect is stronger. In this case both effects seem to be balanced and have similar results to the POM tests. The Plus effect coefficients are -0.04pp and -0.7pp while the Minus effect coefficients are -0.6pp and -0.03pp, with and without controls, respectively. The effects in the separate tests, alike in the POM test, are only statistically significant in the case with control variables and the Plus effect is more significant than the Minus effect.

Control variables are added in regressions (2) and (4) to account for factors that affect net debt issuance other than rating. They are found to be statistically significant across all regressions. *Leverage* has a 3.5pp negative effect on debt issuance; *Profitability* has a 17.1pp positive effect; and *lnSales* has a 0.4pp positive effect. These effects are in line with economic theory as higher leverage, lower sales and lower profitability are associated with lower future debt capacity. Lack of statistical significance for POM, Plus and Minus coefficients without the controls indicates that cross company differences captured by the control variables are crucial in estimating differences in net issuance of debt and the given rating alone does not appear to explain it.

Overall, the results from regressions (1) – (4) imply that companies that have plus or minus credit rating, when accounting for differences in leverage, profitability, and size (*lnSales*), issue less debt than the companies in the middle, neutral group of the broad rating. These findings are in line with Kisgen (2006) who finds that, when accounted for controls, the POM effect is -0.5pp, the Plus effect is -0.1pp, and the Minus effect is -0.4pp. However, in our case the magnitude is larger and there is lower imbalance between the Plus and Minus effects.

5.1.2 Broad Ratings and Interaction Terms

The purpose of these regressions is to analyse the addition of interaction terms effect on the POM, Plus and Minus effects and the impact of the overall rating level. The addition of overall rating level using the *Ranking* variable is important because it can explain how net debt issuance changes as the given rating improves. A detailed description of the variable estimation is presented above in the methodology section. Table 5.2 presents the findings using the broad rating regressions with interaction terms (1I) to (4I).

	(1I)	**(2I)**	**(3I)**	**(4I)**
Intercept	-0.070***	-0.076***	-0.070***	-0.075***
	(0.000)	(0.001)	(0.000)	(0.001)
Ranking	0.004***	0.003***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
CRPOM	-0.029*	-0.040**		
	(0.059)	(0.019)		
CRPlus			-0.051***	-0.056***
			(0.006)	(0.005)
CRMinus			-0.008	-0.023
			(0.647)	(0.266)
CRPOM:Ranking	0.001*	0.002**		
	(0.100)	(0.049)		
CRPlus:Ranking			0.003***	0.003***
			(0.009)	(0.014)
CRMinus:Ranking			0.0002	0.001
			(0.851)	(0.411)
Leverage		-0.029***		-0.030***
		(0.000)		(0.000)
Profitability		0.160***		0.159***
		(0.000)		(0.000)
lnSales		0.001		0.001
		(0.190)		(0.210)
Adj. R^2	0.058	0.124	0.059	0.124
Obs.	2,306	1,766	2,306	1,766

Table 5.2. Broad rating pooled OLS regression results with interaction terms using regressions (1I) – (4I)

From these regressions it is evident that the addition of the interaction terms makes the POM effect higher, which is between -2.9pp and -4.0pp in this case. It is statistically significant both with and without controls. Likewise, the Plus and Minus effects are also larger: The Plus effect ranges from -5.1pp to -5.6pp, and the Minus from -0.8pp to -2.3pp. However, in this case there is a disbalance between the Plus and the Minus effects: The Minus effect is less than half as strong and is not statistically significant while the Plus effect is statistically significant in both regressions. Therefore, it is an indication that, on average, companies seem to be more concerned about the possibility of an upgrade to a higher broad rating category than a downgrade to a lower one. These findings contrast to what Kisgen (2006) observes, where the Minus effect is stronger than the Plus effect. However, it is vital to note that larger POM, Plus and Minus overall coefficients do not necessarily mean a stronger effect in all ratings because the interaction terms and simple coefficients cannot be evaluated in isolation. The true effect must be estimated individually at each rating level by summing the simple and interaction term coefficients.

Moreover, the *Ranking* variable, which ranks all micro ratings from D to AAA, is statistically significant in all regressions. The Ranking effect is positive and fluctuates between 0.3pp and 0.4pp, which means that each improvement in the micro rating is associated with 0.3-0.4pp higher debt issuance. The interaction term with the Plus effect is positive, and the coefficient is 0.3pp in both regressions, which means that the negative Plus effect is reduced by 0.3pp for each rating improvement. E.g., based on regression (4I): When the credit rating is equal to CCC+ (*Ranking* = 10), the total Plus effect is:

$-5.6pp + 10 \times 0.3pp = -2.6pp.$

The Plus interaction term effect is statistically significant in all regressions. Additionally, these results are economically significant with respect to an average debt issuance of 3.9pp, as shown in the provided summary statistics in Appendix 1. The interaction term with the Minus effect is also positive and the coefficients are between 0.02pp and 0.1pp. However, it is not statistically significant in any of the regressions. The POM interaction term effect is statistically significant, and the coefficients fluctuate between 0.1pp and 0.2pp.

Interestingly, the Plus effect inverses with ratings above BBB+ (*Ranking* = 19):

$-5.6pp + 19 \times 0.3pp = 0.1pp.$

This observation illustrates an issue with the interaction terms, that the results of individual ratings can be distorted depending on the *Ranking* variable chosen. This effect is partially a result of relatively large difference between the minimum and maximum values of the variable. We address this problem by proposing an alternative *Ranking* variable. We replace the *Ranking* variable ranging from 1 to 26 with the one ranging from 1 to 10 by eliminating the differences between the Plus, Minus and Neutral ratings and focus only on the broad rating categories. In this case, the inversion effect remains but it is lower and only affects ratings above A. The obtained detailed results are reported in Table 9.19 in Appendix 5.

Regarding the control variables in the regressions (1I) to (4I), the *lnSales* control variable is no longer significant in any of the regressions, which means that some of the effect is explained by the interaction terms and the added *Ranking* variable. This effect is unexpected, as there is no fundamental link between the company rating and its size. This indicates that companies with better rating would also tend to be larger and have larger revenues. Lastly, adjusted R-squared is higher in the regressions with interaction terms. Overall, the interaction term regressions offer an additional perspective on the Plus, Minus, and POM effects and their dependence on the credit rating level. We show that the lower the credit rating, the higher is the effect of Plus and Minus ratings on net issuance of debt.

In summary, the goal of broad ratings regressions is to test the hypotheses H1 - H3, which imply negative POM, Plus and Minus effects, respectively. Our findings indicate that, companies that are close to broad rating upgrade or downgrade, tend to issue less debt, and the effect in the plus rated companies seems to be more evident and pronounced than in the minus ratedones. Therefore, we have enough evidence to accept hypotheses H1 and H2 but not hypothesis H3.

5.2 Micro Ratings Regressions

The aim of the micro ratings regressions is to analyse how companies react when they face a rating upgrade or a downgrade when shifting from one micro rating category to another (i.e. from BBB+ to A-). We expect that the relationship identified in the broad ratings will persist in the micro ratings tests. As described in the methodology section, the regressions with the micro rating entail division of companies within each micro rating into groups based on credit score. The credit score formula is obtained using regression (CS1) and the obtained results are presented in Table 5.3. The results are based on the main data panel, but the findings obtained using alternative data cleaning methods are reported in Appendix 3.

	Full Regression	**Final Regression**
Intercept	-3.972***	-3.649***
	(0.000)	(0.000)
NetIncome/Assets	6.827***	7.535***
	(0.000)	(0.000)
Debt/(Equity + Debt)	-2.083***	-2.514***
	(0.000)	(0.000)
(Debt/(Equity + Debt))^2	0.511**	0.676***
	(0.044)	(0.003)
EBITDA/InterestExpense	-0.007	
	(0.194)	
EBIT/InterestExpense	0.01	
	(0.120)	
lnAssets	0.949***	0.951***
	(0.000)	(0.000)
EBITDA/Assets	5.202***	4.427***
	(0.000)	(0.000)
Adj. R^2	0.418	0.414
Obs.	2,080	2,298

Table 5.3. Credit Score Regressions

We run the regression with all variables to obtain the results illustrated above and then eliminate the variables which are not statistically significant: EBITDA/Interest and EBIT/Interest Expense. Then, we re-run the regression, using only the remaining variables, to obtain the following credit score formula:

$$Score_{t,f} = 7.5\frac{Net\ Income_{t,f}}{Assets_{t,f}} - 2.5\frac{Debt_{t,f}}{Debt_{t,f} + Equity_{t,f}} + 0.7\left(\frac{Debt_{t,f}}{Debt_{t,f} + Equity_{t,f}}\right)^2 + 1.0\ln\left(Assets_{t,f}\right) + 4.4\frac{EBITDA_{t,f}}{Assets_{t,f}}$$

We exclude the intercept as it is a constant and does not affect the division into groups. These coefficients are also logical from an economic perspective: higher net income with respect to assets; lower debt with respect to capital; higher total assets; and higher EBITDA with respect to assets are all associated with better credit ratings. The squared debt over total capital is an indication that debt effect is non-linear, however, overall debt effect remains negative as the coefficient of the squared variable is lower and the values, by definition, fluctuate between 0 and 1. Kisgen (2006) obtains an r-squared of 63.1% in his credit score analysis. Our r-squared measure of 41.4% is slightly lower but is still sufficient to reliably group the companies. The formula based on the results reported in Table 5.3 is used in all subsequent micro rating regressions to group companies into 25% highest and 25% lowest within each micro rating and to obtain the variables *CRHOL*, *CRHigh*, and *CRLow*.

5.2.2 Micro Ratings Regressions

Using the credit scores and grouping of companies within each micro rating, we continue with the micro ratings regressions to test hypotheses H4 - H6 and how debt issuance depends on being among the "best" and the "worst" firms within each rating. Results from OLS regressions (5) – (8) with micro ratings are presented below in Table 5.4.

	(5)	**(6)**	**(7)**	**(8)**
Intercept	0.004**	-0.083***	0.004**	-0.100***
	(0.028)	(0.000)	(0.028)	(0.000)
CRHOL	-0.007***	-0.005**		
	(0.006)	(0.048)		
CRHigh			-0.002	-0.009**
			(0.522)	(0.016)
CRLow			-0.012***	-0.002
			(0.000)	(0.548)
Leverage		-0.034***		-0.035***
		(0.000)		(0.000)
Profitability		0.169***		0.168***
		(0.000)		(0.000)
lnSales		0.004***		0.004***
		(0.000)		(0.000)
Adj. R^2	0.003	0.094	0.006	0.094
Obs.	2,298	1,762	2,298	1,762

Table 5.4. Micro rating pooled OLS regression results using regressions (5) – (8)

The key variables in the micro rating regressions are High or low (HOL), High and Low, which depend on the division into groups within each micro rating group. HOL effect illustrates how the net debt issuance depends on being among top 25% or bottom 25% companies. HOL effect is negative across all regressions and is between -0.5pp and -0.7pp. This effect means that companies among the top 25% and bottom 25% of a micro rating, tend to issue 0.5pp - 0.7pp less net debt with respect to assets. The effect is lower when accounting for control variables and is statistically significant in both regressions. However, the statistical significance is higher when the control variables are excluded, which is primarily a result of the methodology to calculate credit scores, which was used to divide companies into quartiles. Some of the control variables were used to obtain the credit scores, thus if they are not added as separate variables in the regression, the HOL and other effects can be overstated. Therefore, the regressions where controls are accounted for (i.e. regressions 6 and 8) are the most important for the analysis.

As expected, the High and Low effects are negative across all regressions: The High effect is between -0.2pp and -0.9pp while the Low effect is between -0.2pp and -1.2pp, with and without controls respectively. In addition, in contrast to the broad ratings case, the High and Low effects are not balanced. In regression (7) the Low effect is higher and statistically significant while the opposite is the case in regression (8) where the High effect is higher and statistically significant.

Overall, the results seem to indicate that there is a relationship between the ratings and net debt issuance even in the micro rating level. With regards to HOL, companies that are closest to the micro rating upgrade or downgrade tend to issue 0.5-0.7pp less debt than the ones without such proximity to the rating change. These findings seem to mirror the findings made by Kisgen (2006), where the HOL effect was recorded at 1.0pp, the High effect at 0.8pp and the Low effect at 1.0pp. However, in contrast to our findings, he found no significant disbalance between the Low and High effects.

5.2.3 Micro Rating Regressions with Interaction Terms

We implement interaction terms to test whether the abovementioned effects are constant or whether they depend on the micro rating level. Table 5.5 presents the micro rating regression (5I) – (8I) results with interaction terms.

	(5I)	**(6I)**	**(7I)**	**(8I)**
Intercept	-0.060***	-0.066***	-0.060***	-0.040*
	(0.000)	(0.001)	(0.000)	(0.094)
Ranking	0.003***	0.002***	0.003***	0.002***
	(0.000)	(0.003)	(0.000)	(0.000)
CRHOL	-0.052***	-0.066***		
	(0.001)	(0.000)		
CRHigh			-0.025	-0.043*
			(0.163)	(0.051)
CRLow			-0.078***	-0.083***
			(0.000)	(0.000)
CRHOL:Ranking	0.002***	0.003***		
	(0.003)	(0.000)		
CRHigh:Ranking			0.001	0.002**
			(0.190)	(0.049)
CRLow:Ranking			0.004***	0.004***
			(0.000)	(0.000)
Leverage		-0.028***		-0.027***
		(0.000)		(0.000)
Profitability		0.157***		0.160***
		(0.000)		(0.000)
lnSales		0.001		-0.0004
		(0.161)		(0.742)
Adj. R^2	0.061	0.127	0.066	0.129
Obs.	2,298	1,762	2,298	1,762

Table 5.5. Micro rating pooled OLS regression results with interaction terms using regressions (5I) – (8I)

Similarly, as in the broad ratings case, due to the addition of interaction terms, the coefficients of the HOL, High and Low effects increase. The HOL effect is now between -5.2pp and -6.6pp, the High effect between -2.5pp and -4.3pp, and the Low effect between -7.8pp and -8.3pp. HOL is still significant in both regressions. However, there are changes with respect to the significance of High and Low effects as now, the Low effect is statistically significant in both regressions while the High effect is significant only in the (8I) regression. This further implies that the Low effect is stronger than the High effect and indicates that companies may heed the threat of a micro rating downgrade more than an opportunity for an upgrade.

As previously stated, in this case, the HOL, High and Low coefficients by themselves are irrelevant and they must be analysed together with the respective interaction terms. The newly introduced *Ranking* variable is statistically significant in all regressions and the effect is positive between 0.2pp-0.3pp. The HOL, High and Low interaction terms seem to follow similar pattern as in the broad ratings case as the coefficients are always positive: HOL interaction term effect is between 0.2pp and 0.3pp, High between 0.1pp and 0.2pp, and Low effect equals 0.4pp in both regressions. This pattern indicates that the higher the micro rating, the lower the High, Low and HOL effects. However, the High interaction term effect is only statistically significant in the (8I) regression while HOL and Low are significant in both regressions. Furthermore, as in the broad ratings case, overall, HOL, High and Low effects can become positive with a high *Ranking* variable. We address this problem by using an alternative *Ranking* variable where we only consider broad ratings. This alteration reduces the range of the variable from 1 to 26 to 1 to 10 which in turn reduces the inversion effect. The detailed numerical findings are presented in Table 9.19 in Appendix 5.

In summary, the main contribution of the interaction terms regressions in the micro rating case is the identification of the Low effect as stronger than the High effect, which could not be concluded from the initial regressions. The micro rating regressions seem to indicate that HOL effect is prevalent but there is a disbalance between the High and the Low effect. Hypotheses H4 - H6 focus on identification of negative HOL, High and Low effects. Since the HOL and Low effects are negative and statistically significant, there is enough evidence to accept Hypotheses H4 and H6. However, the High effect seems lower and, in many cases, insignificant, which means that hypothesis H5 cannot be accepted with the current evidence.

5.2.4 Comparison with the Broad Rating Regressions

In terms of HOL and POM, both the broad rating and micro rating regressions indicate a similar pattern that companies near a rating upgrade or downgrade tend to issue less debt. The coefficients are similar but the HOL appears to be more statistically significant than the POM. Regarding, the Plus – Minus and High – Low effects, the difference is more evident. In the broad ratings case, there is more evidence to support that companies close to an upgrade issue less debt while the opposite is more pronounced in the micro rating case where there is more evidence to support that companies that are in threat of a downgrade issue less debt.

The coefficients of the control variables and the Ranking variable in the cases with interaction terms seem to be comparable between the broad ratings and the micro ratings regressions. Similarly, the number of active observations and r-squared values are highly similar in both cases, which assures the comparability between the results obtained using the two credit rating methods.

5.3 Fixed Effects Regressions

As outlined in the methodology section, there are some limitations associated with the pooled OLS model. For this reason, we aim to test whether previously outlined pooled OLS regressions are suitable in our case and whether there are any fixed effects. For that, we use the Breusch-Pagan Lagrange Multiplier test, the results of which are presented in Appendix 2. We test for time fixed effects and the obtained results indicate that we can reject the null hypothesis, that there are no significant time fixed effects in all 8 regression forms. Therefore, to account for these effects, we re-run all regressions using the time fixed effects form with clustered standard errors. As mentioned in the methodology, we only focus on the time fixed effects and not firm fixed effects because there are very few observations for each firm, which would lead to insignificant and irrelevant findings. This subsection compares the findings of fixed effects regressions with the previously obtained pooled OLS results. The summary of fixed effects regression results is presented in Tables 5.6 and 5.7 while the Appendix 4 includes a more detailed regression output.

Model	POM	Plus	Minus	POM:R	Plus:R	Minus:R
OLS Results						
Simple	-0.002	-0.0004	-0.003			
Simple + K	-0.007**	-0.007**	-0.006*			
Interaction	-0.029*	-0.051***	-0.008	0.001*	0.003***	0.000
Interaction + K	-0.040**	-0.056***	-0.023	0.002**	0.003***	0.001
FE Results						
Simple	-0.002	-0.001	-0.003			
Simple + K	-0.007**	-0.007**	-0.006*			
Interaction	-0.029	-0.053**	-0.007	0.001	0.003**	0.000
Interaction + K	-0.041*	-0.056**	-0.024	0.002	0.003**	0.001

Table 5.6. OLS and time fixed effects regression comparison using broad ratings.

Model	HOL	High	Low	HOL:R	High:R	Low:R
OLS Results						
Simple	-0.007***	-0.002	-0.012***			
Simple + K	-0.005**	-0.009**	-0.002			
Interaction	-0.052***	-0.025	-0.078***	0.002***	0.001	0.004***
Interaction + K	-0.066***	-0.043*	-0.083***	0.003***	0.002**	0.004***
FE Results						
Simple	-0.008***	-0.003	-0.013***			
Simple + K	-0.006**	-0.011***	-0.001			
Interaction	-0.049***	-0.016	-0.084***	0.002***	0.001	0.004***
Interaction + K	-0.059***	-0.024	-0.085***	0.003***	0.001	0.004***

Table 5.7. OLS and time fixed effects regression comparison using micro ratings.

Regarding the broad rating regressions without interaction terms, a change of model has no major effects on any of the coefficients in the regressions. The statistical significance of POM, Plus and Minus effects is also unchanged, which means that our original findings with regards to these regressions are valid. When we account for interaction terms, again there are no major effects on the obtained coefficients. However, there are some changes regarding the statistical significance. The POM effect and its interaction is statistically significant in all OLS cases while in the fixed effects regression, only the POM effect with controls is significant and not its interaction term with the *Ranking* variable. The Plus effect and its interaction have slightly higher p-values but remain highly statistically significant. The Minus effect and its interaction remain insignificant as before, which means that in the fixed effects case alike in the pooled OLS, there is more evidence to support the Plus effect rather than the Minus effect.

There is a slightly higher absolute effect in the micro ratings than in the broad ratings case however, the coefficients are largely similar. Statistical significance is also unaffected, except for the High effect with interaction terms and controls, which becomes insignificant in the fixed effects case. This leads to even stronger evidence that both HOL and Low effects are present while there is less support for the High effect.

Overall, the fixed effects regressions show greater r-squared and account for the time factor, but they do not alter the main findings from the pooled OLS method. Both POM and HOL effects are present, however, the Plus effect is more prevalent than the Minus effect and the Low effect is more prevalent than the High effect. This means that hypotheses H1, H2, H4 and H6 can be accepted while the hypotheses H3 and H5 lack empirical support.

5.4 Additional Analysis and Robustness Checks

This subsection focuses on the robustness and validity of our main findings. This analysis is done through alternative model specifications, grouping of regressions, and choosing alternative variables and measurements.

5.4.1 Investment Grade Case

Firstly, we analyse a special investment grade case to investigate the effect in the BB and BBB ratings, when the companies shift from investment grade (BBB- and above) to non-investment grade (BB+ and below). This effect arguably should be the strongest as there are significant implications to the access to the credit markets upon this shift (Chernenko & Sunderam, 2012). The obtained results of the pooled OLS and time fixed effects regressions are reported below in Table 5.8. As in the main regressions, we use main data panel, but the alternative data cleaning results are reported in Appendix 5.

	Pooled OLS		**Time Fixed Effects**	
	(3*)	**(4*)**	**(3*)**	**(4*)**
Intercept	-0.034***	-0.033		
	(0.000)	(0.548)		
CRPlus	0.010	0.005	0.009	0.005
	(0.446)	(0.690)	(0.482)	(0.589)
CRMinus	-0.024**	-0.014	-0.019***	-0.016**
	(0.011)	(0.133)	(0.007)	(0.043)
BBB	0.052***	0.042***	0.031***	0.025***
	(0.000)	(0.000)	(0.000)	(0.001)
Leverage		-0.038***		-0.042***
		(0.000)		(0.005)
Profitability		0.283***		0.225***
		(0.000)		(0.000)
lnSales		-0.0004		-0.0004
		(0.853)		(0.789)
Adj. R^2	0.033	0.083	0.066	0.141
Obs.	799	776	712	567

Table 5.8. Investment grade case regressions using pooled OLS and time fixed effects.

In this case the data includes only the companies that are rated BBB, BBB-, BB+, and BB. Therefore, the interpretation of the coefficients is different: default case (intercept) is BB rated companies' net issuance of debt; *CRPlus* represents the BB+ effect; *BBB* represents additional issuance when shifting to BBB rating; and *CRMinus* represents the decrease in debt issuance of BBB- rated companies when compared with the BBB companies

The results indicate that, as expected, BBB and BBB- rated companies issue 2.5pp-5.2pp more debt than BB+ and BB, and this effect is statistically significant at the 1% level. In addition, BBB- companies issue 1.4pp -2.4pp less debt than the BBB ones and this effect is also statistically significant in all regressions, except regression (4*), using pooled OLS. These effects are also economically significant with respect to median debt issuance of 2.3pp and an average of 3.9pp as it is noted in the summary statistics provided in Appendix 1. On the other hand, the *CRPlus* coefficient (BB+ vs BB) is positive and statistically insignificant in all cases. This finding indicates that companies in threat of being downgraded to non-investment grade, issue less debt, however, there is no corresponding evidence for companies that have an opportunity to be upgraded to investment grade.

Interestingly, these results differ from our previous findings with regards to the broad ratings, where we find that the Plus effect seems to be stronger than the Minus effect.

5.4.2 Grouping and Systemising Regressions

By grouping regressions into different categories, we analyse how the findings change across alternative observation samples. The regressions with interaction terms identify the issue that the Plus, Minus, Low and High effects may depend on the rating level. Therefore, we try to address this issue using an alternative approach by dividing the sample into A, B and C rating groups. We find that the results are statistically significant only in the B rating group, which includes all ratings from B- to BBB+ (see Appendix 5 Table 9.18 for detailed results). These results follow expectations as the B group also has the highest number of observations, however, it indicates that there may be more unidentified relationships in other groups.

Furthermore, we find that in the broad ratings case, there is more evidence to support that companies close to an upgrade issue less debt while the opposite is more pronounced in the micro rating case where there is more evidence to support that companies that are in threat of a downgrade issue less debt. Therefore, we aim to test how pronounced are the High and Low effects across three rating groups, namely plus, minus and neutral. We expect that the High effect will be the strongest in the Plus rated companies, and the Low effect the strongest in the Minus rated ones as in this case an upgrade and a downgrade of a micro rating coincides with that of a broad rating. The results reported in Table 9.20 in Appendix 5 show that the strongest effect is the High or upgrade effect in the Plus category. This indicates that companies in our sample tend to issue less debt when they are the closest to a ratings upgrade. However, the Low effect is less evident, and it does not withstand the addition of the control variables.

Finally, we try to identify whether there are any substantial differences in the results before and after the financial crisis of 2008 as well as between different geographic regions. We group the observations into pre-2008 and post-2010 and find largely similar results although significance is reduced in some regressions due to a lower number of observations (see Appendix 5 Table 9.21). This means that the financial crises do not seem to have significantly affected our identified patterns between the issuance of debt and the credit ratings. Moreover, we divide the sample by region to check for regional effects. The results displayed in Table 9.22 in the Appendix 5 show that the identified effects are the most pronounced in the British Isles and least in the Nordic countries.

Overall, grouping of the regressions provides additional insight into the relationship between the net debt issuance and the credit ratings but does not substantially contradict the main findings.

5.4.3 Alternative Regression Specifications

In addition to grouping of observations, we also check alternative model specifications by adding additional terms to the regressions. To check the effect of economic downturns, we add three recession dummy variables that correspond to the recessions of 1990-1991, 2000-2001, and 2008-2010, respectively. The results of this test are shown below in Table 5.9.

	1	**2**	**3**	**4**		**5**	**6**	**7**	**8**
POM	-0.002	-0.007**			**HOL**	-0.007***	-0.005*		
Plus			-0.001	-0.007**	**High**			-0.002	-0.009**
Minus			-0.003	-0.006*	**Low**			-0.012***	-0.002
Recession1	-0.026	0.007	-0.025	0.007	**Recession1**	-0.026	0.005	-0.022	0.003
Recession2	-0.006	-0.009	-0.006	-0.009	**Recession2**	-0.006	-0.009	-0.004	-0.01
Recession3	-0.011***	-0.009**	-0.011***	-0.009**	**Recession3**	-0.011***	-0.009**	-0.012***	-0.009**

Table 5.9. Regressions with added recession terms 1(1990-1991), 2(2000-2001), 3(2008-2010).

We observe no substantial change in significance or effect size in the broad rating or micro rating tests. In addition, recessions (1) and (2) are not significant and do not seem to impact net issuance of debt. However, during recession (3), the financial crisis of 2008-2010, there is significantly less debt issued which is along with expectations.

Interestingly, if we add an investment grade (*IG*) dummy variable to the regressions, which allocates a value of 1 to all observations with credit ratings of BBB+ and above. The obtained results are reported in Table 5.10.

	1	**2**	**3**	**4**		**5**	**6**	**7**	**8**
POM	-0.001	-0.008			**HOL**	-0.019***	-0.020***		
Plus			-0.0002	-0.006	**High**			-0.008	-0.015**
Minus			-0.003	-0.013	**Low**			-0.031***	-0.025***
IG	0.037***	0.027***	0.037***	0.027***	**IG**	0.026***	0.018***	0.026***	0.019***
POM:IG	-0.003	0.001			**HOL:IG**	0.015**	0.018***		
Plus:IG			-0.0002	0.0000	**High:IG**			0.007	0.014*
Minus:IG			-0.004	0.005	**Low:IG**			0.023***	0.021**

Table 5.10. Regressions with added investment grade (IG) interaction terms

In the micro ratings case, we find strong support for HOL, High and Low effects, all of which are negative as expected. In addition, the positive coefficients of the interaction terms regression indicate that these effects are substantially stronger in the ratings below investment grade. On the other hand, none of the effects remain significant in the broad ratings case. This finding contradicts expectations and may indicate that the effects are captured by the investment grade dummy variable. However, while the investment grade dummy could partially explain the Minus effect, as lower rated companies issue less debt, it cannot explain the Plus effect. These findings are contradictory to our main results; however, our observations are concentrated in the ratings close to a shift from investment to non-investment grades, which may cause bias in the regressions with investment grade dummies.

5.4.4 Robustness Checks

As a final step to evaluate the robustness of our findings, we conduct a set of robustness checks by addressing the issues related to the balance sheet and credit rating input variables used in the main broad rating and micro rating models. Tables 5.11 and 5.12 present the summary of all robustness checks analysed in this part.

Check	POM	POM + K	Plus	Minus	Plus + K	Minus + K	No. obs.
Original Results	**-0.002**	**-0.007****	**-0.0004**	**-0.003**	**-0.007****	**-0.006***	**2,306/1,766**
Alternative debt measure	-0.006	-0.010***	-0.006	-0.006	-0.011**	-0.010**	1,970/1,766
No equity issuance	-0.002	-0.005**	-0.0002	-0.004	-0.004	-0.007**	2,306/1,766
Market value for equity	0.928	1.021	0.516	1.376	0.536	1.594	1,621/1,459
Original balance sheet	-0.001	-0.007**	-0.0003	-0.001	-0.008**	-0.006*	2,306/1,760
Foreign rating	-0.002	-0.007**	-0.0004	-0.003	-0.007**	-0.006*	2,306/1,766
Exclude rating assignment year	-0.002	-0.007**	-0.0004	-0.003	-0.007**	-0.006*	2,306/1,766
Exclude Financial Sector	-0.001	-0.006*	0.0004	-0.004	-0.006*	-0.006	1,815/1,507

Table 5.11. Broad Rating robustness checks.

Check	HOL	HOL + K	High	Low	High + K	Low + K	No. obs.
Original Results	**-0.007*****	**-0.005****	**-0.002**	**-0.012*****	**-0.009****	**-0.002**	**2,298/1,762**
Alternative debt measure	-0.010***	-0.006	-0.008**	-0.011**	-0.014***	0.003	1,964/1,762
No equity issuance	-0.004**	-0.004*	-0.002	-0.007**	-0.010***	0.001	2,298/1,762
Market value for equity	-0.584	-0.623	-0.395	-0.751	0.015	-1.16	1,616/1,456
Original balance sheet	-0.005**	-0.004	-0.0004	-0.010***	-0.008**	0.0001	2,300/1,757
Foreign rating	-0.035***	-0.036***	-0.0002	-0.011***	-0.007*	-0.001	2,234/1,704
Exclude rating assignment year	-0.008***	-0.007***	-0.003	-0.013***	-0.009**	-0.007*	1,673/1,325
Alternative Ranking measure	-0.007***	-0.005*	-0.002	-0.012***	-0.009**	-0.001	2,283/1,749
1/3 – 1/3 thresholds for scores	-0.004	-0.004	-0.0002	-0.008***	-0.008**	0.0003	2,298/1,762
0.15 - 0.15 thresholds for scores	-0.006**	-0.003	-0.001	-0.011***	-0.008*	0.001	2,298/1,762
Exclude Financial Sector	-0.009***	-0.008***	-0.001	-0.015***	-0.014***	-0.003	1,810/1,503

Table 5.12. Micro Rating robustness checks.

We start by addressing the dependent variable, net issuance of debt, which is measured as net issuance (retirement) of debt minus net issuance (retirement) of equity divided by total assets. One way to adjust this variable is to estimate issuance of debt as a first difference of total debt, which means that we account for cases where net issuance data is unavailable or unreliable. Our results are largely robust to this check in both broad and micro rating regressions. Coefficients of most variables increase, and the statistical significance remains largely unchanged. The HOL test with controls becomes insignificant while the significance of High test without controls improves.

We also conduct a similar test regarding the issuance of equity. We cannot replace the equity issuance using first difference of total equity as it is affected not only by changes in shareholder's equity but also by net income and reclassifications. Therefore, one option is to eliminate the equity issuance and only check the debt changes as a proportion of total assets. It is unclear if equity issuances are connected to debt issuances in terms of rating strategy. We find that the findings are largely robust to this change, the sign of the coefficients remains negative as expected and the same variables are statistically significant, except for the Plus effect with controls which becomes statistically insignificant.

Withal, as is argued in the data section, the ratings are largely based on book numbers and that is indeed the focus of this paper as well as Kisgen's (2006). To add to the evaluation of the strength of the dependent variable proxy, we examine whether using a market measure for equity impacts the results as the market values are often considered in valuations of companies. It is noteworthy that often, the trading currency and the reporting currency differ, and we only analyse the cases where these currencies match to avoid the exchange rate translation bias. However, this alteration leads to insignificant and economically invalid results and we cannot reliably account for the market values.

Despite the results from the market value tests, we can largely conclude that the dependent variable is a capable and robust proxy to account for the net issuance of debt. We also argue that the restated balance sheet data used in the original regressions is the most prudent because the effects we study are long-term processes that in most cases will already be based already on the restated values rather than the originally reported numbers. However, as a final balance sheet data quality check, we collect original balance sheet data and re-run our regressions. We find that this change eliminates significance in the HOL with controls test but the results remain otherwise unchanged. Thus, we conclude that our usage of blanace sheet data is appropriate.

Having addressed the balance sheet and the dependent variable concern, we focus on the rating variables. As described in the data section, we use domestic credit ratings in our original models. However, we also collect the foreign ratings and run the same regressions using them as a quality check. There is almost complete overlap between the two categories, so the results are largely similar. Moreover, companies may decide to issue debt or change their capital policies immediately after the rating change. To account for this issue, we eliminate the years when the rating was issued and only focus on the period following the rating announcement. Our findings indicate an attained significance in the Low effect with controls, but the results remain otherwise unchanged. Consequently, we are confident with the quality of the ratings data.

The credit score is the most discretionary variable we use. Thus, we take several measures to check its validity. Notwithstanding the regressions described in the methodology section as to how to develop it, we also subject it to some further robustness checks. Firstly, our observations of ratings are not evenly distributed, and there are gaps in some rating categories near the ends of the spectrum. To alleviate potential skewness arising from this and to test if there are any effect on the results, we recreate the credit score by instead using only the ratings from CCC- to AA+, where there are no gaps, in the *Ranking* variable. The results are largely robust even though significance is reduced in the HOL test with controls.

Furthermore, when we calculate the credit score, we split the observations in each micro rating into quartiles in order to have as many observations in the high or low category as in the neutral category. This approach is a diversion from Kisgen (2006) who uses thirds, so for transparency we recalculate the groups based on thirds in line with Kisgen (2006). Division into thirds is also in line with the broad ratings where plus, minus and neutral ratings are split into almost even thirds as it is shown in summary statistics in Appendix 1. The findings show that the significance is reduced, especially in the HOL test where the results are insignificant. This reduction in significance is explained by the fact that more observations near the “middle” are moved into the HOL group and they would be expected to be less constrained in their debt issuance due to lower proximity to a rating change. We subsequently perform a check in the other direction and divide the companies in each micro rating into top and bottom 15%. While the results hold stronger than in the tests with thirds, several observations are lost as the number of observations required within each micro rating for construction of the credit score increases and the results are still less significant than in our main regressions.

As our final robustness check, we address an issue that our original sample includes the financial sector, which is commonly excluded in the capital structure research but is kept by Kisgen (2006). Using Thomson Reuters industry classification, we eliminate the financial sector companies and find that the results stay robust with an exception of the Minus effect with controls. Furthermore, the significance of the findings in the micro rating regressions is highly improved.

In summary, the additional models as well as the robustness checks show that our findings are not limited to single model specification and the identified relationships between the net issuance of debt, and that the proximity to the credit ratings change withstands a number of tests and adjustments.

5.5 Results Summary

The goal of the analysis described in this subsection is to summarise the tests of the six abovementioned hypotheses. Hypotheses H1 to H3 focus on the broad ratings while the hypotheses H4 to H6 focus on the micro ratings, aiming to identify whether proximity to a rating change leads to a lower debt issuance in hopes to facilitate an upgrade or prevent a downgrade. The summary of the approved hypotheses in each model is provided in Table 5.13.

Hypotheses	OLS	OLS + K	OLS + I	OLS + I + K	FE	FE + K	FE + I	FE + I + K
H1(POM)	•	•	•	•		•		•
H2(Plus)		•	•	•		•	•	•
H3(Minus)		•				•		
H4(HOL)	•	•	•	•	•	•	•	•
H5(High)		•		•		•		
H6(Low)	•		•	•	•		•	•

Table 5.13 Results Summary, approved hypotheses by model.

To test hypotheses H1 – H6, we analyse broad ratings and micro ratings using pooled OLS (OLS) and fixed effects models (FE) with time fixed effects. We perform all regressions with and without controls (K) as well as with and without interaction terms (I). The main findings with regards to the broad ratings indicate that there is a prevalent POM effect, which means that companies that are close to a broad rating upgrade or downgrade tend to issue less debt. However, the results seem to indicate that there is a disbalance between the significance of Plus and Minus effects and the former one is more evident. Therefore, we accept hypotheses H1 and H2, which focus on the POM and the Plus effects but not H3, which focuses on the Minus effect.

Regarding the micro rating regressions, we find very strong evidence to support the HOL effect, which means that the top and bottom quartiles of companies (ranked by credit score) tend to issue less debt in hopes to gain a micro rating upgrade or avoid a downgrade. However, there is a disbalance between the High and Low effects, both in terms of coefficients and the statistical significance. There seems to be more evidence to approve the HOL and the Low effects, namely hypotheses H4 and H6 while the High effect or hypothesis H5 may need further research.

The interaction term regressions (I) provide additional insight into how the issuance of debt is related to the broad and micro ratings. Our results indicate that the overall effect of key variables is highly dependent on the rating level. The lower the rating is, the stronger are the POM, Plus, Minus, HOL, High, and Low effects.

We have also conducted a series of additional model specification and robustness checks to test the validity and consistency of our findings. In summary, our models withstand most of these checks and our obtained results are robust and reliable.

6. Results Discussion

6.1 Results Interpretation

6.1.1 Main Findings

Our research questions build upon an affluent body of research in the field of capital structure and an increasing body in the field of credit ratings. We aim to continue to bridge the gap between these fields and explain how they entwine. To help further the research on the link between the two fields, we investigate the capital structure decisions that firms near rating changes make compared to those firms not near a rating change.

This thesis, in part, follows the methodology of Kisgen (2006). Kisgen's (2006) and our results demonstrate a clear difference in capital structure behaviour by those firms near a rating change, indicated by a lower issuance of debt compared to their peers. The effect is visible both in the broad ratings and micro ratings. Furthermore, our findings are economically and statistically significant. Our results show that that this behaviour exists on a global scale and over a longer timeframe than previously shown by Kisgen (2006).

An onstream issue in Kisgen's (2006) regressions is that the model implies that the behaviour studied is non-time varying. We expand on this issue with a fixed effects model and recession terms that account for these effects, which increases the significance of the results. Furthermore, we widen Kisgen's (2006) research by investigating if the effect differs across ratings by adding the rating as an interaction term. And indeed, we find that the effect is stronger the lower the rating and that investment grade level acts as a cut off.

6.1.2 Implications for Capital Structure and Credit Ratings Theory

Our research shows a clear connection between capital structure behaviour and credit ratings. The fact that companies accommodate credit rating information in their capital structure decisions strengthens the link between these fields. This calls for credit rating implications to be considered in future capital structure research. Furthermore, credit ratings research should consider the leverage constraints companies may conform to when evaluating credit ratings' effect on company behaviour.

Traditionally, the trade-off theory stipulates that companies optimise their capital structure with regard to tax shield and cost of financial distress (Miller, 1977; Myers, 2001). Later research has shown that factors such as taxes, type of debt, asset quality and probability of bankruptcy (Leland, 1994; Frank and Goyal, 2009) also play a role. Our findings do not contradict the trade-off theory bur rather show that credit rating is yet another factor to consider and may drive companies toward detrimental capital structure. This observation presents opportunities to incorporate credit ratings into research about the trade-off theory.

Contrastingly, the pecking order theory states that companies finance investments at the lowest possible cost of capital (Myers, 2001). Frank and Goyal (2003) find that the theory lost accuracy over time and that the effect is more pronounced in larger companies. Potentially, our results add a potential control variable in pecking order studies as credit rating concern may be a reason companies stray from the pecking order theory estimations.

Overall, our findings do not contradict current capital structure or credit rating theory but suggests credit ratings and ratings change proximity could be an additional factor to consider in capital structure research.

6.1.3 Wider Implications

Common for all our results is that they show a negative coefficient. Even in the case where significance is lacking, the results imply a negative effect on issuance of debt in the case of proximity to a rating change, both in the case of broad ratings and in the case of micro rating. This effect points strongly to the presence of an awareness of credit rating implications in capital structure decisions, is in line with expectations and coheres to the results of Kisgen (2009) who shows that firms indeed adjust behaviour to target credit ratings and Alissa et al. (2013) who find that firms use earnings management to align results with credit rating expectations. It is also feasible in terms of the model constructed by Boot et al. (2006) that outlines that ratings serve as a coordinating mechanism between investors and companies. Additionally, these results mean that companies and CRAs work in conjunction and not independent of one another. Credit ratings should be viewed in the context that companies try to maximise them, and regulators should recognize this. Furthermore, as companies act to lower their cost of capital, and since cost of capital is driven by investor sentiment, which in turn is affected by credit ratings, it follows that companies strategize their rating. This affects how CRAs should operate and their overall function. A credit rating should reflect a company's overall economic fundamentals as well as measures taken to manipulate the credit rating. Moreover, the fact that companies change capital structure to affect ratings may cause them to diverge from optimal capital structure which in turn leads to inefficient use of resources.

Furthermore, our research is interesting for investors that use credit ratings for guidance in investment decisions to factor that companies strategize regarding their rating. As we outline in section 2, many investors are also restricted by rating in their investments, so these findings pertain to them as well as regulators that regulate such investment thresholds.

Lastly, since leverage is an important measure of risk and credit ratings primarily measure risk of credit loss, it is a sign of a well-functioning apparatus that companies close to a rating change withhold from issuing debt as to maintain their rating. Decreasing (maintaining) leverage decreases (maintains) the risk level, therefore, it is apt that those companies are rewarded with a more favourable rating.

6.2 Limitations and opportunities for further research

Besides the potential issues addressed previously in the robustness checks, our research is subject to limitations. Firstly, as we have limited access to the data on defunct companies, our results are affected by survivorship bias. Surviving companies may have different debt policies than existing companies in each period. However, our observations are skewed towards more recent observations, which reduces the likelihood that a significant proportion of firms are unobserved. In addition, our results might be skewed towards smaller rated companies as these companies are more numerous in the sample even though their economic significance is smaller.

Furthermore, we primarily use company level S&P credit ratings, which omits observations by other rating agencies and bond-level rating data. This approach reduces the sample size and may impose omitted variable bias, when companies consider ratings of other agencies. On the other hand, inclusion of such information could lead to other types of bias resulting from data filtering and data matching. Moreover, potentially there is reverse causality between rating changes and debt issuance. Companies may have their ratings changed due to their existing debt policies. However, as we use prevailing ratings, in many cases for more than one year, the reverse causality issue is unlikely to affect the results.

In addition to the limitations, there are other substantial opportunities for further research in the field. So far there has been limited research on credit ratings and capital structure outside the US, and there are numerous opportunities to identify global patterns as well as cross country differences. To address the different time periods and identify breaks due to changes in regulations, financial markets and other factors may also lead to novel findings. Furthermore, as debt is utilized differently across sectors, it could be useful to conduct sector specific analysis by focusing on financial, non-financial, physical capital-intensive and human capital-intensive companies. Lastly, the results are sensitive to the measurements of debt issuance and further research could target these measures as well as focus on differences in debt types, such as bank debt versus bonds.

7. Conclusion

In this paper we have aimed to investigate the role of credit ratings in capital structure decisions. Ratings and rating agencies have been a prominent part of the global financial system for many decades and there has been substantial amount of research that addresses credit ratings' importance for investors. Therefore, as companies are highly dependent on investors' opinion, outlook and valuations when they access capital markets, it is natural that assigned credit ratings play a key role in how companies act. However, so far, the credit rating effects on rated firms have not been analysed thoroughly. This research is not only important for investors and companies, but also for other financial institutions, such as banks, insurance companies, and regulators as via this channel, credit rating agencies can have a systematic impact.

We have approached this topic by analysing how companies' net issuance of debt with respect to assets is affected by their prevailing S&P credit rating. We have aimed to expand Kisgen's (2006) research of US companies and focus on Northern European rated firms from 1990 to 2018. Our main research question is "Do companies close to a rating upgrade or downgrade issue less debt?" As debt and credit ratings are closely related, we expect that companies will adjust their debt policies based on the given rating and those which are close to an upgrade will issue less debt in hopes of being upgraded while those close to a downgrade will also issue less debt to avoid the potential rating downgrade.

We analysed our data sample using pooled OLS and time fixed effects methods. We found that companies close to an upgrade or downgrade tend to issue less debt and this pattern is evident in both micro ratings (e.g. from BB to BB+) and broad ratings (e.g. from BB to BBB). These findings are in line with previous research and we have showed that the relationship identified by Kisgen (2006) is still present. However, tests which aim to analyse upgrade and downgrade effects in isolation have been inconclusive. We found that the potential upgrade effect is more prevalent in the broad ratings tests while the potential downgrade is more prevalent in the micro ratings tests. Therefore, there are opportunities for further research, which could address issues such as other rating agencies, bond ratings, different types of debt as well as sector specific analysis. Such research would benefit the further understanding of capital structure decisions with credit rating concerns as well as help assess the power and systematic impact of credit rating agencies.

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9. Appendices

Appendix 1. Summary Statistics

	NetDI	| NetDI |	POM	Plus	Minus	HOL	High	Low
Average	-0.004	0.039	0.672	0.356	0.315	0.504	0.253	0.252
Median	0.000	0.023	-	-	-	-	-	-
St. Dev.	0.067	0.055	-	-	-	-	-	-
Min	-1.197	0.000	0	0	0	0	0	0
Max	0.294	1.197	1	1	1	1	1	1
1st quartile	-0.023	0.007	-	-	-	-	-	-
3rd quartile	0.024	0.054	-	-	-	-	-	-
Observations	4043	4043	2306	2306	2306	2298	2298	2298
Count*	-	-	1549	822	727	1159	581	578

Table 9.1. Summary Statistics of key variables using the main panel. Count refers to dummy variables equal to 1.

Appendix 2. BPLM Test Results

No.	Regression	Chi-sq statistic	p-value
(1)	$NetDI_{t,f}=\beta_0+\beta_1 CRPOM_{t,f}+\varepsilon_{t,f}$	68.298	< 2.2e-16
(2)	$NetDI_{t,f}=\beta_0+\beta_1 CRPOM_{t,f}+\beta_2 Leverage_{t,f}+\beta_2 Profitability_{t,f}+\beta_3 lnSales_{t,f}+\varepsilon_{t,f}$	133.3	< 2.2e-17
(3)	$NetDI_{t,f}=\beta_0+\beta_1 CRPlus_{t,f}+\beta_2 CRMinus_{t,f}+\varepsilon_{t,f}$	68.569	< 2.2e-18
(4)	$NetDI_{t,f}=\beta_0+\beta_1 CRPlus_{t,f}+\beta_2 CRMinus_{t,f}+\beta_3 Leverage_{t,f}+\beta_4 Profitability_{t,f}+\beta_5 lnSales_{t,f}+\varepsilon_{t,f}$	133.44	< 2.2e-19
(5)	$NetDI_{t,f}=\beta_0+\beta_1 CRHOL_{t,f}+\varepsilon_{t,f}$	75.774	< 2.2e-20
(6)	$NetDI_{t,f}=\beta_0+\beta_1 CRHOL_{t,f}+\beta_2 Leverage_{t,f}+\beta_3 Profitability_{t,f}+\beta_4 lnSales_{t,f}+\varepsilon_{t,f}$	138.97	< 2.2e-21
(7)	$NetDI_{t,f}=\beta_0+\beta_1 CRHigh_{t,f}+\beta_2 CRLow_{t,f}+\varepsilon_{t,f}$	75.143	< 2.2e-22
(8)	$NetDI_{t,f}=\beta_0+\beta_1 CRHigh_{t,f}+\beta_2 CRLow_{t,f}+\beta_3 Leverage_{t,f}+\beta_4 Profitability_{t,f}+\beta_5 lnSales_{t,f}+\varepsilon_{t,f}$	144.46	< 2.2e-23

Table 9.2. Breusch-Pagan Lagrange Multiplier test results for time fixed effects. H0: there are no time fixed effects.

Appendix 3. Regression results across all panels

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Intercept	0.006*	-0.048*	0.006**	-0.12***	0.001	-0.09***
	(0.079)	(0.069)	(0.027)	(0.000)	(0.534)	(0.000)
CRPOM	-0.002	-0.006	-0.001	-0.007*	-0.002	-0.007**
	(0.534)	(0.140)	(0.884)	(0.060)	(0.510)	(0.017)
Leverage		-0.057***		-0.073***		-0.035***
		(0.000)		(0.000)		(0.000)
Profitability		0.235***		0.170***		0.171***
		(0.000)		(0.000)		(0.000)
lnSales		0.002**		0.006***		0.004***
		(0.035)		(0.000)		(0.000)
Adj. R^2	-0.0002	0.082	-0.0004	0.122	-0.0002	0.094
Obs.	2,516	2,279	2,366	1,970	2,306	1,766
	(3)	**(4)**	**(3)**	**(4)**	**(3)**	**(4)**
Intercept	0.006*	-0.048*	-0.006**	-0.12***	0.001	-0.089***
	(0.079)	(0.070)	(0.027)	(0.000)	(0.534)	(0.000)
CRPlus	-0.001	-0.007	0.002	-0.006	-0.0004	-0.007**
	(0.735)	(0.111)	(0.609)	(0.134)	(0.890)	(0.026)
CRMinus	-0.003	-0.004	-0.003	-0.008*	-0.003	-0.006*
	(0.451)	(0.357)	(0.412)	(0.073)	(0.295)	(0.058)
Leverage		-0.057***		-0.073***		-0.035***
		(0.000)		(0.000)		(0.000)
Profitability		0.235***		0.169***		0.171***
		(0.000)		(0.000)		(0.000)
lnSales		0.002**		0.006***		0.004***
		(0.035)		(0.000)		(0.000)
Adj. R^2	-0.001	0.082	-0.001	0.122	-0.0003	0.093
Obs.	2,516	2,279	2,366	1,970	2,306	1,766

Table 9.3. Broad rating pooled OLS regression results across all panels using regressions (1) – (4)

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(1I)	**(2I)**	**(1I)**	**(2I)**	**(1I)**	**(2I)**
Intercept	-0.078***	-0.036	-0.122***	-0.110***	-0.070***	-0.076***
	(0.000)	(0.220)	(0.000)	(0.000)	(0.000)	(0.001)
Ranking	0.005***	0.004***	0.006***	0.004***	0.004***	0.003***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
CRPOM	-0.024	-0.024	-0.029	-0.040*	-0.029*	-0.040**
	(0.273)	(0.304)	(0.126)	(0.058)	(0.059)	(0.019)
CRPOM:Ranking	0.001	0.001	0.001	0.002	0.001*	0.002**
	(0.380)	(0.447)	(0.180)	(0.116)	(0.100)	(0.049)
Leverage		-0.051***		-0.063***		-0.029***
		(0.000)		(0.000)		(0.000)
Profitability		0.220***		0.150***		0.160***
		(0.000)		(0.000)		(0.000)
lnSales		-0.001		0.002		0.001
		(0.406)		(0.124)		(0.190)
Adj. R^2	0.032	0.095	0.081	0.155	0.058	0.124
Obs.	2,516	2,279	2,366	1,970	2,306	1,766
	(3I)	**(4I)**	**(3I)**	**(4I)**	**(3I)**	**(4I)**
Intercept	-0.078***	-0.035	-0.122***	-0.110***	-0.070***	-0.075***
	(0.000)	(0.232)	(0.000)	(0.000)	(0.000)	(0.001)
Ranking	0.005***	0.004***	0.006***	0.004***	0.004***	0.003***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
CRPlus	-0.035	-0.029	-0.042*	-0.042*	-0.051***	-0.056***
	(0.190)	(0.292)	(0.069)	(0.091)	(0.006)	(0.005)
CRPlus:Ranking	0.002	0.001	0.002*	0.002	0.003***	0.003***
	(0.251)	(0.443)	(0.082)	(0.154)	(0.009)	(0.014)
CRMinus	-0.014	-0.020	-0.018	-0.038	-0.008	-0.023
	(0.575)	(0.475)	(0.428)	(0.129)	(0.647)	(0.266)
CRMinus:Ranking	0.0005	0.001	0.001	0.002	0.0002	0.001
	(0.720)	(0.571)	(0.587)	(0.215)	(0.851)	(0.411)
Leverage		-0.051***		-0.063***		-0.030***
		(0.000)		(0.000)		(0.000)
Profitability		0.220***		0.149***		0.159***
		(0.000)		(0.000)		(0.000)
lnSales		-0.001		0.002		0.001
		(0.390)		(0.127)		(0.210)
Adj. R^2	0.031	0.095	0.081	0.154	0.059	0.124
Obs.	2,516	2,279	2,366	1,970	2,306	1,766

Table 9.4. Broad rating pooled OLS regression results across all panels with interaction terms using regressions (1I) – (4I)

	Full Regression			Final Regression		
	Panel A	**Panel B**	**Main Panel**	**Panel A**	**Panel B**	**Main Panel**
Intercept	-3.520***	-3.848***	-3.972***	-3.710***	-3.879***	-3.649***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NetIncome/Assets	7.653***	7.587***	6.827***	8.297***	7.945***	7.535***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt/(Equity + Debt)	-0.862***	-1.415***	-2.083***	-0.612***	-1.336***	-2.514***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Debt/(Equity + Debt))^2	-0.042***	-0.071***	0.511**	-0.026***	-0.067***	0.676***
	(0.000)	(0.000)	(0.044)	(0.000)	(0.000)	(0.003)
EBITDA/InterestExpense	0.005	0.004	-0.007			
	(0.169)	(0.394)	(0.194)			
EBIT/InterestExpense	-0.003	-0.002	0.01			
	(0.468)	(0.716)	(0.120)			
lnAssets	0.923***	0.939***	0.949***	0.931***	0.945***	0.951***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA/Assets	1.732***	3.590***	5.202***	1.932***	3.545***	4.427***
	(0.007)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Adj. R^2	0.401	0.412	0.418	0.390	0.405	0.414
Obs.	3,125	2,769	2,080	3,481	3,057	2,298

Table 9.5. Credit Score Regressions across all panels.

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(5)	**(6)**	**(5)**	**(6)**	**(5)**	**(6)**
Intercept	0.010***	-0.038	-0.001	-0.113***	0.004**	-0.083***
	(0.0001)	(0.146)	(0.659)	(0.000)	(0.028)	(0.000)
CRHOL	-0.011***	-0.009***	-0.010***	-0.007**	-0.007***	-0.005**
	(0.002)	(0.022)	(0.002)	(0.047)	(0.006)	(0.048)
Leverage		-0.056***		-0.071***		-0.034***
		(0.000)		(0.000)		(0.000)
Profitability		0.229***		0.165***		0.169***
		(0.000)		(0.000)		(0.000)
lnSales		0.002*		0.005***		0.004***
		(0.076)		(0.000)		(0.000)
Adj. R^2	0.004	0.082	0.004	0.120	0.003	0.094
Obs.	2,507	2,274	2,357	1,965	2,298	1,762
	(7)	**(8)**	**(7)**	**(8)**	**(7)**	**(8)**
Intercept	0.010***	-0.018	-0.001	-0.148***	0.004**	-0.100***
	(0.000)	(0.561)	(0.658)	(0.000)	(0.028)	(0.000)
CRHigh	-0.006	-0.004	-0.002	-0.014***	-0.002	-0.009**
	(0.187)	(0.411)	(0.626)	(0.003)	(0.522)	(0.016)
CRLow	-0.017***	-0.012**	-0.019***	-0.0004	-0.012***	-0.002
	(0.000)	(0.012)	(0.000)	(0.936)	(0.000)	(0.548)
Leverage		-0.056***		-0.072***		-0.035***
		(0.000)		(0.000)		(0.000)
Profitability		0.232***		0.162***		0.168***
		(0.000)		(0.000)		(0.000)
lnSales		0.001		0.007***		0.004***
		(0.419)		(0.000)		(0.000)
Adj. R^2	0.005	0.083	0.010	0.122	0.006	0.094
Obs.	2,507	2,274	2,357	1,965	2,298	1,762

Table 9.6. Micro rating pooled OLS regression results across all panels using regressions (5) – (8)

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(5I)	**(6I)**	**(5I)**	**(6I)**	**(5I)**	**(6I)**
Intercept	-0.064***	-0.024	-0.104***	-0.101***	-0.060***	-0.066***
	(0.000)	(0.392)	(0.000)	(0.001)	(0.000)	(0.001)
Ranking	0.004***	0.003***	0.005***	0.004***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
CRHOL	-0.051**	-0.047**	-0.064***	-0.068***	-0.052***	-0.066***
	(0.018)	(0.040)	(0.001)	(0.002)	(0.001)	(0.000)
CRHOL:Ranking	0.002*	0.002*	0.003***	0.003***	0.002***	0.003***
	(0.064)	(0.088)	(0.004)	(0.003)	(0.003)	(0.000)
Leverage		-0.050***		-0.060***		-0.028***
		(0.000)		(0.000)		(0.000)
Profitability		0.214***		0.142***		0.157***
		(0.000)		(0.000)		(0.000)
lnSales		-0.001		0.002		0.001
		(0.387)		(0.107)		(0.161)
Adj. R^2	0.034	0.096	0.085	0.155	0.061	0.127
Obs.	2,507	2,274	2,357	1,965	2,298	1,762
	(7I)	**(8I)**	**(7I)**	**(8I)**	**(7I)**	**(8I)**
Intercept	-0.064***	0.052	-0.104***	-0.072**	-0.060***	-0.040*
	(0.000)	(0.116)	(0.000)	(0.017)	(0.000)	(0.094)
Ranking	0.004***	0.004***	0.005***	0.004***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CRHigh	-0.012	0.005	-0.011	-0.023	-0.025	-0.043*
	(0.643)	(0.856)	(0.630)	(0.395)	(0.163)	(0.051)
CRHigh:Ranking	0.0003	0.0001	0.0005	0.001	0.001	0.002**
	(0.824)	(0.948)	(0.680)	(0.421)	(0.190)	(0.049)
CRLow	-0.086***	-0.079***	-0.116***	-0.101***	-0.078***	-0.083***
	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
CRLow:Ranking	0.004***	0.003**	0.005***	0.005***	0.004***	0.004***
	(0.007)	(0.031)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage		-0.048***		-0.058***		-0.027***
		(0.000)		(0.000)		(0.000)
Profitability		0.221***		0.149***		0.160***
		(0.000)		(0.000)		(0.000)
lnSales		-0.006***		0.00001		-0.0004
		(0.001)		(0.997)		(0.742)
Adj. R^2	0.037	0.102	0.094	0.157	0.066	0.129
Obs.	2,507	2,274	2,357	1,965	2,298	1,762

Table 9.7. Micro rating pooled OLS regression results across all panels with interaction terms using regressions (5I) – (8I)

Appendix 4. Fixed effects regressions across all panels

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
CRPOM	-0.002	-0.005	-0.001	-0.007	-0.002	-0.007**
	(0.549)	(0.252)	(0.848)	(0.103)	(0.467)	(0.031)
Leverage		-0.054**		-0.071***		-0.033***
		(0.015)		(0.006)		(0.005)
Profitability		0.227***		0.170***		0.173***
		(0.000)		(0.000)		(0.000)
lnSales		0.003*		0.006***		0.004***
		(0.083)		(0.000)		(0.000)
Adj. R^2	0.03	0.11	0.022	0.148	0.023	0.130
Obs.	2,516	2,279	2,366	1,970	2,306	1,766
	(3)	**(4)**	**(3)**	**(4)**	**(3)**	**(4)**
CRPlus	-0.001	-0.007	0.002	-0.006	-0.001	-0.007**
	(0.743)	(0.199)	(0.690)	(0.182)	(0.791)	(0.030)
CRMinus	-0.003	-0.004	-0.003	-0.007*	-0.003	-0.006*
	(0.485)	(0.492)	(0.401)	(0.089)	(0.263)	(0.083)
Leverage		-0.055**		-0.071***		-0.033***
		(0.015)		(0.006)		(0.005)
Profitability		0.227***		0.170***		0.173***
		(0.000)		(0.000)		(0.000)
lnSales		0.003*		0.006***		0.004***
		(0.084)		(0.000)		(0.000)
Adj. R^2	0.030	0.110	0.022	0.147	0.023	0.129
Obs.	2,516	2,279	2,366	1,970	2,306	1,766

Table 9.8. Broad rating time fixed effects regression results across all panels using regressions (1) – (4)

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(1I)	**(2I)**	**(1I)**	**(2I)**	**(1I)**	**(2I)**
Ranking	0.005***	0.004***	0.007***	0.005***	0.005***	0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
CRPOM	-0.023	-0.022	-0.03	-0.04	-0.029	-0.041*
	(0.470)	(0.496)	(0.241)	(0.181)	(0.158)	(0.082)
CRPOM:Ranking	0.001	0.001	0.001	0.002	0.001	0.002
	(0.542)	(0.582)	(0.277)	(0.227)	(0.204)	(0.121)
Leverage		-0.047**		-0.060**		-0.026***
		(0.027)		(0.014)		(0.010)
Profitability		0.216***		0.156***		0.165***
		(0.000)		(0.000)		(0.000)
lnSales		-0.001		0.001		0.001
		(0.328)		(0.182)		(0.434)
Adj. R^2	0.062	0.125	0.115	0.188	0.093	0.170
Obs.	2,516	2,279	2,366	1,970	2,306	1,766
	(3I)	**(4I)**	**(3I)**	**(4I)**	**(3I)**	**(4I)**
Ranking	0.005***	0.004***	0.007***	0.005***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CRPlus	-0.034	-0.026	-0.045*	-0.043	-0.053**	-0.056**
	(0.378)	(0.508)	(0.099)	(0.185)	(0.022)	(0.024)
CRPlus:Ranking	0.002	0.001	0.002*	0.002	0.003**	0.003**
	(0.411)	(0.610)	(0.092)	(0.227)	(0.023)	(0.038)
CRMinus	-0.012	-0.019	-0.014	-0.037	-0.007	-0.024
	(0.759)	(0.629)	(0.625)	(0.295)	(0.794)	(0.409)
CRMinus:Ranking	0.0003	0.001	0.0004	0.002	0.00004	0.001
	(0.856)	(0.668)	(0.773)	(0.364)	(0.977)	(0.527)
Leverage		-0.048**		-0.060**		-0.027***
		(0.027)		(0.014)		(0.010)
Profitability		0.216***		0.156***		0.164***
		(0.000)		(0.000)		(0.000)
lnSales		-0.001		0.001		0.001
		(0.310)		(0.174)		(0.484)
Adj. R^2	0.062	0.125	0.116	0.187	0.095	0.170
Obs.	2,516	2,279	2,366	1,970	2,306	1,766

Table 9.9. Broad rating time fixed effects regression results across all panels with interaction terms using regressions (1I) – (4I)

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(5)	**(6)**	**(5)**	**(6)**	**(5)**	**(6)**
CRHOL	-0.011***	-0.009**	-0.011***	-0.007**	-0.008***	-0.006**
	(0.004)	(0.018)	(0.000)	(0.014)	(0.000)	(0.015)
Leverage		-0.053**		-0.069***		-0.032***
		(0.015)		(0.007)		(0.004)
Profitability		0.221***		0.165***		0.170***
		(0.000)		(0.000)		(0.000)
lnSales		0.002		0.006***		0.004***
		(0.124)		(0.000)		(0.000)
Adj. R^2	0.034	0.111	0.027	0.146	0.028	0.131
Obs.	2,507	2,274	2,357	1,965	2,298	1,762
	(7)	**(8)**	**(7)**	**(8)**	**(7)**	**(8)**
CRHigh	-0.005	-0.005	-0.002	-0.016***	-0.003	-0.011***
	(0.120)	(0.305)	(0.283)	(0.000)	(0.199)	(0.002)
CRLow	-0.018***	-0.012*	-0.020***	0.001	-0.013***	-0.001
	(0.006)	(0.060)	(0.000)	(0.839)	(0.000)	(0.887)
Leverage		-0.053**		-0.070***		-0.033***
		(0.015)		(0.007)		(0.005)
Profitability		0.223***		0.164***		0.171***
		(0.000)		(0.000)		(0.000)
lnSales		0.001		0.008***		0.005***
		(0.450)		(0.000)		(0.000)
Adj. R^2	0.036	0.111	0.032	0.149	0.030	0.132
Obs.	2,507	2,274	2,357	1,965	2,298	1,762

Table 9.10. Micro rating time fixed effects regression results across all panels using regressions (5) – (8)

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(5I)	**(6I)**	**(5I)**	**(6I)**	**(5I)**	**(6I)**
Ranking	0.004***	0.004***	0.007***	0.005***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CRHOL	-0.047**	-0.041	-0.060**	-0.064***	-0.049***	-0.059***
	(0.050)	(0.111)	(0.019)	(0.008)	(0.001)	(0.000)
CRHOL:Ranking	0.002*	0.002	0.003**	0.003***	0.002***	0.003***
	(0.094)	(0.161)	(0.034)	(0.010)	(0.003)	(0.000)
Leverage		-0.046**		-0.057**		-0.025***
		(0.027)		(0.015)		(0.007)
Profitability		0.210***		0.149***		0.162***
		(0.001)		(0.000)		(0.000)
lnSales		-0.001		0.001		0.001
		(0.310)		(0.162)		(0.367)
Adj. R^2	0.065	0.126	0.119	0.188	0.097	0.173
Obs.	2,507	2,274	2,357	1,965	2,298	1,762
	(7I)	**(8I)**	**(7I)**	**(8I)**	**(7I)**	**(8I)**
Ranking	0.004***	0.005***	0.007***	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CRHigh	-0.002	0.014	0.001	-0.007	-0.016	-0.024
	(0.915)	(0.573)	(0.976)	(0.793)	(0.377)	(0.324)
CRHigh:Ranking	-0.0003	-0.0005	-0.0003	0.0001	0.001	0.001
	(0.797)	(0.683)	(0.797)	(0.932)	(0.527)	(0.378)
CRLow	-0.090**	-0.077*	-0.123***	-0.108***	-0.084***	-0.085***
	(0.046)	(0.075)	(0.002)	(0.002)	(0.002)	(0.000)
CRLow:Ranking	0.004*	0.003	0.006***	0.005***	0.004***	0.004***
	(0.058)	(0.127)	(0.003)	(0.002)	(0.003)	(0.000)
Leverage		-0.045**		-0.056**		-0.025***
		(0.028)		(0.018)		(0.007)
Profitability		0.215***		0.157***		0.166***
		(0.000)		(0.000)		(0.000)
lnSales		-0.005***		0.0001		-0.0003
		(0.007)		(0.939)		(0.788)
Adj. R^2	0.068	0.130	0.127	0.191	0.101	0.175
Obs.	2,507	2,274	2,357	1,965	2,298	1,762

Table 9.11. Micro rating time fixed effects regression results across all panels with interaction terms using regressions (5I) – (8I)

Appendix 5. Additional Specifications and Robustness Checks

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(3*)	(4*)	(3*)	(4*)	(3*)	(4*)
Intercept	-0.034***	-0.033	-0.007	0.026	-0.024***	-0.035
	(0.000)	(0.548)	(0.347)	(0.573)	(0.001)	(0.370)
CRPlus	0.010	0.005	-0.005	-0.008	0.008	0.007
	(0.446)	(0.690)	(0.659)	(0.473)	(0.376)	(0.492)
CRMinus	-0.024**	-0.014	-0.018**	-0.012	-0.019***	-0.017***
	(0.011)	(0.133)	(0.015)	(0.120)	(0.004)	(0.008)
BBB	0.052***	0.042***	0.028***	0.019**	0.029***	0.025***
	(0.000)	(0.000)	(0.003)	(0.048)	(0.000)	(0.004)
Leverage		-0.038***		-0.043***		-0.028***
		(0.000)		(0.000)		(0.000)
Profitability		0.283***		0.361***		0.224***
		(0.000)		(0.000)		(0.000)
lnSales		-0.0004		-0.002		0.0003
		(0.853)		(0.297)		(0.869)
Adj. R^2	0.033	0.083	0.020	0.124	0.023	0.082
Obs.	799	776	765	664	712	567

Table 9.12. Investment grade case regressions across all panels using pooled OLS.

	Panel A: no exclusions		Panel B: debt issues > 10% excluded		Main Panel: debt and equity issues > 10% excluded	
	(3*)	(4*)	(3*)	(4*)	(3*)	(4*)
CRPlus	0.015	0.009	-0.002	-0.008	0.009	0.005
	(0.441)	(0.609)	(0.856)	(0.514)	(0.482)	(0.589)
CRMinus	-0.020**	-0.011	-0.017**	-0.011	-0.019***	-0.016**
	(0.021)	(0.266)	(0.029)	(0.290)	(0.007)	(0.043)
BBB	0.054***	0.043***	0.028***	0.019**	0.031***	0.025***
	(0.000)	(0.001)	(0.003)	(0.040)	(0.000)	(0.001)
Leverage		-0.038		-0.058***		-0.042***
		(0.170)		(0.002)		(0.005)
Profitability		0.288***		0.350***		0.225***
		(0.004)		(0.000)		(0.000)
lnSales		0.0002		-0.003*		-0.0004
		(0.899)		(0.058)		(0.789)
Adj. R^2	0.082	0.133	0.070	0.182	0.066	0.141
Obs.	799	776	765	664	712	567

Table 9.13. Investment grade case regressions across all panels using time fixed effects.

Check	POM	POM + K	Plus	Minus	Plus + K	Minus + K	No. obs.
Original Results	**-0.002**	**-0.007****	**-0.0004**	**-0.003**	**-0.007****	**-0.006***	**2,306/1,766**
Alternative debt measure	-0.006	-0.010***	-0.006	-0.006	-0.011**	-0.010**	1,970/1,766
No equity issuance	-0.002	-0.005**	-0.0002	-0.004	-0.004	-0.007**	2,306/1,766
Alternative equity measure	-0.004	-0.007	-0.005	-0.003	-0.008	-0.006	1,970/1,766
Exclude rating assignment year	-0.002	-0.007**	-0.0004	-0.003	-0.007**	-0.006*	2,306/1,766
Foreign rating	-0.002	-0.007**	-0.0004	-0.003	-0.007**	-0.006*	2,306/1,766
Original balance sheet	-0.001	-0.007**	-0.0003	-0.001	-0.008**	-0.006*	2,306/1,760
Market value for equity	0.928	1.021	0.516	1.376	0.536	1.594	1,621/1,459
Exclude Financial Sector	-0.001	-0.006*	0.0004	-0.004	-0.006*	-0.006	1,815/1,507

Table 9.14. Broad Rating robustness checks.

Check	HOL	HOL + K	High	Low	High + K	Low + K	No. obs.
Original Results	**-0.007*****	**-0.005****	**-0.002**	**-0.012*****	**-0.009****	**-0.002**	**2,298/1,762**
Alternative Ranking measure	-0.007***	-0.005*	-0.002	-0.012***	-0.009**	-0.001	2,283/1,749
Alternative debt measure	-0.010***	-0.006	-0.008**	-0.011**	-0.014***	0.003	1,964/1,762
No equity issuance	-0.004**	-0.004*	-0.002	-0.007**	-0.010***	0.001	2,298/1,762
Alternative equity measure	0.006	0.005	-0.004	0.017***	-0.031***	0.037***	1,964/1,762
Exclude rating assignment year	-0.008***	-0.007***	-0.003	-0.013***	-0.009**	-0.007*	1,673/1,325
Foreign rating	-0.035***	-0.036***	-0.0002	-0.011***	-0.007*	-0.001	2,234/1,704
Original balance sheet	-0.005**	-0.004	-0.0004	-0.010***	-0.008**	0.0001	2,300/1,757
Market value for equity	-0.584	-0.623	-0.395	-0.751	0.015	-1.16	1,616/1,456
1/3 – 1/3 thresholds for scores	-0.004	-0.004	-0.0002	-0.008***	-0.008**	0.0003	2,298/1,762
0.15 - 0.15 thresholds for scores	-0.006**	-0.003	-0.001	-0.011***	-0.008*	0.001	2,298/1,762
Exclude Financial Sector	-0.009***	-0.008***	-0.001	-0.015***	-0.014***	-0.003	1,810/1,503

Table 9.15. Micro Rating robustness checks.

	1	2	3	4		5	6	7	8
POM	-0.002	-0.007**			**HOL**	-0.007***	-0.005*		
Plus			-0.001	-0.007**	**High**			-0.002	-0.009**
Minus			-0.003	-0.006*	**Low**			-0.012***	-0.002
Recession1	-0.026	0.007	-0.025	0.007	**Recession1**	-0.026	0.005	-0.022	0.003
Recession2	-0.006	-0.009	-0.006	-0.009	**Recession2**	-0.006	-0.009	-0.004	-0.01
Recession3	-0.011***	-0.009**	-0.011***	-0.009**	**Recession3**	-0.011***	-0.009**	-0.012***	-0.009**

Table 9.16. Regressions with added recession terms 1(1990-1991), 2(2000-2001), 3(2008-2010).

	1	2	3	4		5	6	7	8
POM	-0.001	-0.008			**HOL**	-0.019***	-0.020***		
Plus			-0.0002	-0.006	**High**			-0.008	-0.015**
Minus			-0.003	-0.013	**Low**			-0.031***	-0.025***
IG	0.037***	0.027***	0.037***	0.027***	**IG**	0.026***	0.018***	0.026***	0.019***
POM:IG	-0.003	0.001			**HOL:IG**	0.015**	0.018***		
Plus:IG			-0.0002	0.0000	**High:IG**			0.007	0.014*
Minus:IG			-0.004	0.005	**Low:IG**			0.023***	0.021**

Table 9.17. Regressions with added investment grade (IG) interaction terms

Check	POM	POM + K	Plus	Minus	Plus + K	Minus + K	No. obs.
Original Results	**-0.002**	**-0.007****	**-0.0004**	**-0.003**	**-0.007****	**-0.006***	**2,306/1,766**
A	-0.001	-0.002	0.006	-0.005	0.003	-0.004	974/720
B	-0.004	-0.010**	0.0002	-0.013**	-0.008*	-0.014***	1,323/1,039
C	-0.078	-0.075	-0.121	-0.012	-0.142	-0.029	9/7
	HOL	**HOL + K**	**High**	**Low**	**High + K**	**Low + K**	**No. obs.**
Original Results	**-0.007*****	**-0.005****	**-0.002**	**-0.012*****	**-0.009****	**-0.002**	**2,298/1,762**
A	-0.001	0.0003	0.001	-0.003	0.001	0.00001	972/720
B	-0.011***	-0.008**	-0.004	-0.018***	-0.007	-0.010*	1,317/1,035
C	-0.130*	-0.031	-0.081	-0.180**	-0.006	-0.100	9/7

Table 9.18. Regressions in separated panels by rating group.

	1	2	3	4		5	6	7	8
POM	-0.021	-0.039**			**HOL**	-0.058***	-0.070***		
Plus			-0.054***	-0.060***	**High**			-0.029	-0.052**
Minus			-0.015	-0.031	**Low**			-0.088***	-0.083***
Ranking	0.011***	0.008***	0.011***	0.008***	**Ranking**	0.009***	0.006***	0.009***	0.007***
POM:Ranking	0.002	0.004*			**HOL:Ranking**	0.007***	0.009***		
Plus:Ranking			0.008***	0.008**	**High:Ranking**			0.004	0.007**
Minus:Ranking			0.001	0.003	**Low:Ranking**			0.010***	0.010***

Table 9.19. Interaction term regressions with added alternative ranking measure: no rank difference between plus, minus and neutral of each broad rating. Original regressions are reported in Tables 5.2 and 5.5.

Check	HOL	HOL + K	High	Low	High + K	Low + K	No. obs.
Original Results	**-0.007*** **	**-0.005** **	**-0.002**	**-0.012*** **	**-0.009** **	**-0.002**	**2,298/1,762**
Plus	-0.009**	-0.005	-0.003	-0.016***	-0.015***	0.005	819/670
Minus	-0.006	-0.008	-0.002	-0.011**	-0.006	-0.009	725/526
Neutral	-0.005	-0.001	-0.002	-0.009	-0.006	0.003	754/566

Table 9.20. Micro rating regressions in separated panels by micro rating type: plus, minus and neutral are analysed separately.

Check	POM	POM + K	Plus	Minus	Plus + K	Minus + K	No. obs.
Original Results	**-0.002**	**-0.007** **	**-0.0004**	**-0.003**	**-0.007** **	**-0.006***	**2,306/1,766**
Pre-crisis (2008)	-0.003	-0.007	0.002	-0.008	-0.004	-0.012**	910/695
Post-crisis (2010)	-0.003	-0.006	-0.004	-0.001	-0.009**	-0.002	1,150/894
	HOL	**HOL + K**	**High**	**Low**	**High + K**	**Low + K**	**No. obs.**
Original Results	**-0.007*** **	**-0.005** **	**-0.002**	**-0.012*** **	**-0.009** **	**-0.002**	**2,298/1,762**
Pre-crisis (2008)	-0.011***	-0.006	0.0004	-0.017***	-0.003	-0.008	907/693
Post-crisis (2010)	-0.003	-0.005	-0.001	-0.008*	-0.009**	0.001	1,146/893

Table 9.21. Regressions in separated panels into pre and post-crisis periods.

Check	POM	POM + K	Plus	Minus	Plus + K	Minus + K	No. obs.
Original Results	**-0.002**	**-0.007** **	**-0.0004**	**-0.003**	**-0.007** **	**-0.006***	**2,306/1,766**
Nordics	-0.005	-0.005	-0.001	-0.009	-0.005	-0.004	492/335
British Isles	-0.005	-0.013***	-0.002	-0.008*	-0.011**	-0.015***	1,103/867
DE + NL	0.009**	0.003	0.007	0.011**	0.001	0.005	711/564
	HOL	**HOL + K**	**High**	**Low**	**High + K**	**Low + K**	**No. obs.**
Original Results	**-0.007*** **	**-0.005** **	**-0.002**	**-0.012*** **	**-0.009** **	**-0.002**	**2,298/1,762**
Nordics	-0.003	-0.009	-0.002	-0.01	-0.009	-0.005	491/335
British Isles	-0.014***	-0.010**	-0.003	-0.018***	-0.012*	-0.009**	1,098/864
DE + NL	-0.002	0.002	-0.004	0.0002	-0.009	0.014**	709/563

Table 9.22. Regressions in separated panels by regions.