The Effect of Credit Rating Discontinuity on Firms' Capital Structure

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Abstract

This dissertation compares rated and formerly rated firms regarding their capital structure. Using a panel dataset from 1991 to 2014, I estimate the effect of credit rating discontinuity on firms' debt-to-equity issuance, leverage, net debt issuance, and cash holdings as proxies for their capital structure decisions. I use a set of OLS regressions with established control variables and employ time, firm, and industry fixed effects. The results suggest that we do observe rating discontinuity within this sample and that firms experiencing periods without S&P rating and continuously rated firms present differences in capital structure. Firms with rating discontinuity show lower debt-to-equity issuance, lower leverage, less net debt issuances, and higher cash holdings than continuously rated firms. These effects strengthen over time. However, this work cannot finally prove the existence of rating discontinuity. Without assuming that ratings from other CRAs are perfect substitutes for S&P ratings, there is still the possibility of other aspects, like issuer shopping, causing those differences in capital structure. Further, the findings suggest a small reputation effect on net debt issuance and leverage levels. The results are robust to changes in leverage definitions and the addition of rating and investment grade information to the models.

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Resumo

A presente dissertação tenciona comparar empresas com e sem classificações de crédito com à sua estrutura de capital. Este estudo é realizado com dados, que incluem o período entre 1991 e 2014. Estimo o efeito da descontinuidade da classificação de crédito sobre a emissão de dívida em relação ao capital próprio, a alavancagem, a emissão de dívida e a disponibilidade de tesouraria. Utilizo um conjunto de regressões MQO com variáveis de controle e uso efeitos fixos de tempo, empresa e setor. Os resultados sugerem a presença da descontinuidade da classificação e que as empresas que passam por períodos sem classificação da S&P têm diferenças na estrutura de capital. As empresas com descontinuidade de classificação apresentam menor emissão de dívida em relação ao patrimônio líquido, menor alavancagem, menor emissão de dívida líquida e uma maior disponibilidade de tesouraria do que as empresas com classificação contínua. Esses efeitos se fortalecem com o tempo. Entretanto, este trabalho não pode finalmente provar a existência da descontinuidade da classificação. Sem presumir que as classificações de outras CRAs sejam substitutos perfeitos para as classificações da S&P, ainda existe a possibilidade de, por exemplo, o efeito de compras como causa dessas diferenças na estrutura de capital. Além disso, os resultados sugerem um pequeno efeito da reputação sobre a emissão de dívida líquida e os níveis de alavancagem. Os resultados são robustos em relação às mudanças nas definições de alavancagem e à adição de informações de classificação e grau de investimento aos modelos.

Título: O efeito da descontinuidade da classificação de crédito na estrutura de capital das empresas

Autor: Christian Haverkamp

Palavras-chave: Classificação de crédito, Descontinuidade de classificação de crédito, Estrutura de capital, Emissão de dívida, Emissão de ações, Alavancagem, Disponibilidade de tesouraria

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1. Introduction

Financial research has always been interested in understanding the different factors that impact the financing decisions of firms. According to Graham & Harvey (2001), managers are concerned with the trade-off between the tax benefits and the costs of financial distress associated with debt financing and consider credit ratings as essential signals to investors. This has led to increasing research on the impact of credit ratings on firms' capital structure.

Kisgen (2006) and Faulkender & Petersen (2006) show that firms reduce their leverage following credit rating downgrades, and firms with higher ratings demonstrate lower cost of debt. However, some firms used to have a credit rating from Standards & Poor's (S&P) but decided to suspend their rating for some years, discontinue it completely, or suspend their rating and obtain a rating from a different credit rating agency (CRA). One reason for this could be that firms want to save money or anticipate a more favorable rating from another agency. Such behavior is called 'shopping effect' or 'issuer shopping' (Bolton et al., 2012). Another reason could be that firms foresee a reputation effect, meaning that having a long rating history lets investors perceive them as a 'good' company making a credit rating obsolete in the future.

My dissertation focuses on the following aspects: first, I test whether the capital structure of firms rated and formerly rated by S&P differs. The hypothesis is that rating discontinuity does have an impact because it should limit firms' ability to access the debt market and increase financing costs. The second hypothesis is that there is no credit rating shopping if we see differences in capital structure between those two groups. If firms switch to a different CRA, we should not observe any impact on their capital structure. Further, I want to test whether the reputation of firms, meaning a long-standing rating history, impacts its capital structure. This research contributes to the existing literature by providing valuable insights into the factors influencing firms' financing decisions, with important implications for companies, policymakers, and investors who seek to make informed choices regarding firms' capital structure.

In this dissertation, I analyze credit ratings issued by S&P and compare rated and formerly rated firms concerning their capital structure. Depending on the model, firms with rating discontinuity show 1.2 to 1.9 percentage points lower debt-to-equity issuance, 8.1 to 13.3 percentage points lower book leverage, 7.2 to 11.6 percentage points lower market leverage, 1.6 to 2.2 percentage points smaller net debt issuance and 0.9 to 4.4 percentage points higher cash holdings. All these effects are large and do not occur immediately after rating discontinuity but strengthen over time. At the same time, these results suggest that those firms discontinued their rating and did not switch to another CRA. However, I cannot prove this, because the interpretation is subject to the assumption that investors perceive ratings from CRAs other than S&P as perfect substitutes which might not be true. Regarding the reputation effect, the findings suggest a small impact on net debt issuance and leverage levels.

In terms of the structure of this dissertation, I start with a thorough review of the existing literature on credit ratings and firms' capital structure. Then, I present the methodology and data I employ for my analysis. The results section presents the discontinuity effects on firms' debt-to-equity issuance, leverage, net debt issuance, and cash holdings. Finally, I discuss the main limitations, present potential future research, and summarize the main conclusions.

2. Literature Review

Capital structure theory is a fundamental research area in corporate finance that explains how companies finance their investments and operations. Donaldson (1961) first introduces the pecking order theory that suggests that companies prefer to avoid external funding, especially equity. Firms rather have a hierarchy of financing sources, choosing internal financing first, then debt, and finally equity as a last resort. Further, firms consider debt financing because of the tax deductibility of interest payments (Modigliani & Miller, 1963). Later, Kraus & Litzenberger (1973) state that firms set a target debt-to-value ratio and then move closer to it over time by weighing the benefits of debt tax shields against bankruptcy costs. The signaling theory imposes another impact on firms' capital structure decisions. By having one party send a signal that would disclose some pertinent information to the other party, two parties could get around the issue of asymmetric information (Spence, 1973).

The ability of an entity to fulfill its financial obligations is evaluated through a credit rating. Organizations that assess a company's creditworthiness or a financial instrument are known as credit rating agencies (CRAs). Credit ratings are typically expressed as letter grades ranging from 'AAA' (investment grade) to 'D' (default) to communicate the agency's opinion of the relative level of credit risk. In the US, where this study focuses on, CRAs must be registered by the Securities and Exchange Commission (SEC) as 'nationally recognized statistical rating organizations (NRSRO) (Credit Rating Agency Reform Act, 2006). Standard & Poor's (S&P), Moody's, and Fitch are the leading Credit Rating Agencies. Those Credit Rating Agencies have various functions. According to Millon & Thakor (1985), credit rating agencies have access to information that is not public. They serve as efficient aggregators and distributors of information. The agencies provide reliable information that helps market participants to make informed decisions.

Furthermore, the agencies' certification function is used for capital allocation and regulatory purposes (Credit Rating Agency Reform Act, 2006). Boot et al. (2006) note that credit rating agencies play a monitoring role, providing ongoing evaluation of creditworthiness and potential risks associated with issuers and issues. There are, however, concerns and criticism since credit rating agencies are typically compensated by the issuers whose securities they rate. This incentive structure can result in rating agencies assigning more favorable ratings than warranted to maintain existing clients and attract new ones (Bolton et al., 2012; Mason & Rosner, 2007).

In their survey, Graham & Harvey (2001) first highlight the importance of corporate credit ratings and their potential impact on companies' financing decisions. Managers are concerned with the trade-off between the tax benefits and the costs of financial distress associated with debt financing. For them, credit ratings are essential indicators of potential problems. Kisgen (2006) first provides empirical evidence that credit ratings impact firms' capital structure. This is supported by Faulkender & Petersen (2006), who find that high ratings positively impact the cost of debt. Further, firms reduce their leverage following credit rating downgrades. The effect is even more prominent when a firm's rating is downgraded to speculative grade and when commercial paper access is affected. At the same time, rating upgrades do not trigger subsequent capital structure changes (Huang & Shen, 2015; Kisgen, 2006). Alp (2013), Baghai et al. (2014), and Jorion et al. (2009), who analyze the time-series variation in issuer credit ratings, demonstrate that grading criteria have become more stringent over time. Firms impacted by this increased conservatism issue less debt, have lower leverage, and hold more cash (Baghai et al., 2014). In addition, firms' financing and investment decisions are not only impacted by individual firm-specific credit ratings but also by sovereign rating downgrades (Almeida et al., 2017). Kisgen (2019) also shows that credit rating agencies' assessment methodology to determine their ratings affects capital structure. Firms' capital structure is impacted to different extents, and firms adjust it at varying speeds after a rating change (Wojewodzki et al., 2018). The impact on firms in countries with more market-oriented financial systems and strong legal and institutional environments is more significant, and firms rated 'speculative grade' react more rapidly to a rating change (Huang & Shen, 2015; Wojewodzki et al., 2018).

3. Methodology and Data

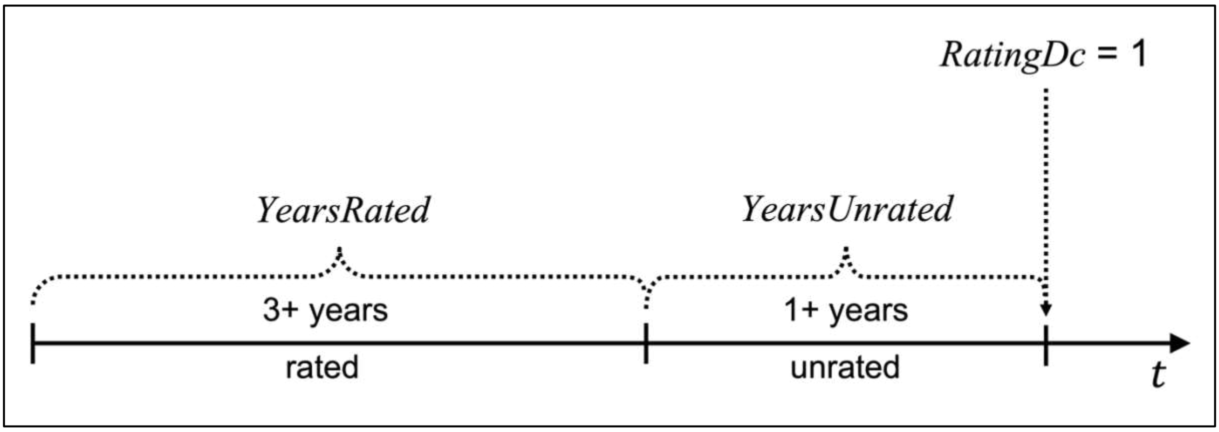
This section explains my research question and how I test my hypotheses. Further, I explain the data collection and cleaning process and present descriptive statistics for the generated sample.

3.1. Methodology

I create three main explanatory variables to test whether the capital structure of firms with rating discontinuity is different and whether there might be a shopping or reputational effect (see Figure 1). To identify rating discontinuity, I create *RatingDc* as a dummy variable that takes the value of one for firm-years where a firm was rated by S&P for at least three consecutive years followed by at least one unrated year from S&P. Since *RatingDc* will be equal to one in all years after rating discontinuity, I create the *YearsUnrated* variable to measures the years between when a firm became unrated and the time of the observation t. To capture a potential reputational effect, I use the *YearsRated* variable to measure the number of consecutive years a firm has a credit rating. The dependent variables are debt in relation to equity issuance, leverage, net debt issuance and cash holdings as proxies for the capital structure of firms. I use the same control variables as Baghai et al. (2014). All variable definitions can be found in Table I. For variables that represent variations over time (e.g., debt and equity issuance) and because *RatingDc* requires firms to present at least one year without a rating, variables in these models are lagged by one period to account for endogeneity.

Figure 1 – Definition of *RatingDc*, *YearsUnrated,* and *YearsRated*

This figure shows the definition of the three variables *RatingDc*, *YearsRated,* and *YearsUnrated* for an observation where the *RatingDc* variable equals one. That is when a firm used to be rated for at least three years in the past and discontinued its rating for more than one year. *YearsRated* measures the consecutive years a firm has a credit rating. *YearsUnrated* measures the time between the year when a firm became unrated and the time of the observation t.



I use Ordinary Least Squared (OLS) regressions on my panel data to assess the relationship between my dependent and independent variables. I control for unobserved heterogeneity by employing year-fixed, firm-fixed, and/or industry-fixed effects (FE). To test the impact of rating discontinuity, I employ the following regression equations for each of my dependent variables:

1) $\Upsilon_{i,t} = \beta_0 + \beta_1 \times RatingDc_{i,t} + \epsilon_{i,t}$

2) $\Upsilon_{i,t} = \beta_0 + \beta_1 \times RatingDc_{i,t} + \beta_2 \times Controls_{i,t} + \epsilon_{i,t}$

3) $\Upsilon_{i,t} = \beta_0 + \beta_1 \times RatingDc_{i,t} + \beta_2 \times Controls_{i,t} + \delta_t + \epsilon_{i,t}$

4) $\Upsilon_{i,t} = \beta_0 + \beta_1 \times RatingDc_{i,t} + \beta_2 \times Controls_{i,t} + \sigma_i + \epsilon_{i,t}$

5) $\Upsilon_{i,t} = \beta_0 + \beta_1 \times RatingDc_{i,t} + \beta_2 \times Controls_{i,t} + \delta_t + \sigma_i + \epsilon_{i,t}$

6) $\Upsilon_{i,t} = \beta_0 + \beta_1 \times RatingDc_{i,t} + \beta_2 \times Controls_{i,t} + \gamma_i + \epsilon_{i,t}$

7) $\Upsilon_{i,t} = \beta_0 + \beta_1 \times RatingDc_{i,t} + \beta_2 \times Controls_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t}$

Where i represents the individual firm and t the period for which the data is collected. δ represents the Year FE, γ the Industry FE, σ the Firm FE, and ϵ the error term.

In the second step, I analyze whether the number of years a firm is not rated anymore, captured by *YearsUnrated,* impacts its capital structure. I use the same regression models described in 1) to 7) but with $YearsUnrated_{i,t}$ as the key explanatory variable. In the third model, I use *YearsRated* to capture a potential reputation effect. A higher value of *YearsRated* implies a longer rating history for a firm. Thus, it might have established a reputation due to the provided stability of information. Based on this, investors may perceive them as lower-risk borrowers, which could result in easier access to capital and reduced need for new debt issuance. To test this, I use the same regression models as described in 1) to 7) but with $YearsRated_{i,t}$ as the key explanatory variable.

I perform two robustness tests for each model to round off my analysis. I add two new control variables (*LastRating* and *LastInvGrade)* to the regressions. The *LastRating* variable represents the last available credit rating from S&P received by a firm. According to existing literature, firms with lower last available ratings should present, for example, higher leverage levels. *LastInvGrade* is a dummy variable based on *LastRating* and takes one if the respective firm was last rated as investment grade and zero otherwise. The beforementioned effect should be even more noticeable as investment-grade firms generally are more creditworthy. By adding these two variables, I want to ensure that my results are not only driven by the rating information or the investment grade. Standard errors are clustered at the firm level for all my regressions to adjust for heteroskedasticity and autocorrelation.

3.2. Data

I gather Standard & Poor's ratings data from the Compustat Ratings database for the sample period from 1986 to 2016. I use the domestic long-term issuer credit rating commonly used by prior literature since it presents the longest available timespan for ratings (Baghai et al., 2014; Berger et al., 1997; Kisgen, 2006; Titman & Wessels, 1988). I remove firms with the SIC codes 4900-4999 (utilities), 6000-6999 (financial institutions), and SIC codes above 9000 (government-related firms) from my sample. I only keep firms that are rated for at least three consecutive years. I combine the Compustat data with financial statement data from CRSP/Compustat, and I keep only one observation per firm and year. Since I also use industry fixed effects in my regression, I obtain the North American Industry Classification System (NAICS) codes from CRSP and extract the first two digits which identify the NAICS sectors, standing for broad groups of economic activities, i.e., industries (NAICS, 2022).

The dependent variables are debt in relation to equity issuance, leverage, net debt issuance and cash holdings as proxies for the capital structure of firms. *DebtToEquityIssuance i*s long-term debt issuance minus long-term debt reduction plus changes in current debt minus the sale of common and preferred stock minus the purchase of common and preferred stock divided by total assets. *BookLev* is long- and short-term debt divided by total assets, *MktLev* is total interest-bearing debt divided by the sum of total interest-bearing debt and market equity*, NetDebtIssuance is* defined as long-term debt issues minus long-term debt reductions minus current debt changes divided by total assets and *Cash/Assets* is cash and marketable securities divided by total assets. I select the control variables based on prior literature, which are used in the different models. These variables are: (1) *Rating* is the domestic long-term issuer credit rating from Standard & Poor's, converted into a numerical scale where each number represents one notch (i.e., AAA is 1, AA+ is 2, etc., C is equal to 21). Firms rated D (default) are excluded from the sample. (2) *MarketToBook* is the ratio of the book value of assets plus the market value of equity minus the book value of common equity minus balance sheet deferred taxes to the book value of assets. (3) *PPE/Assets* is the net property, plant, and equipment divided by total assets. (4) *Profit* is EBITDA divided by sales. (5) *Size* is the log of the book value of assets in constant 2005 dollars. (6) *Carryfwd/Asset* is computed as tax loss carryforwards divided by total assets. Following prior literature, missing values of carryforward tax losses were replaced by zero. (7) *R&D/Sales* the ratio of R&D expenditures to total sales. Missing values of R&D are also replaced with zero. (8) *CAPEX/Sales* is capital expenditures divided by sales. (9) *Acq/Sales* is cash acquisitions divided by sales. (10) *NWC/Assets* is net working capital less cash divided by assets. (11) *Vol* is the volatility of profitability, which is computed as rolling volatility over the current period and four previous periods[1]. (12) *DivDummy* is a dummy variable that takes one for years in which a firm pays a common dividend, zero otherwise. All variables are winsorized at the 95th percentile to account for outliers within the sample. *DebtToEquityIssuance*, *MarketToBook*, *NWC/Assets*, *Profit*, and *Vol*, are also winsorized at the 5th percentile.

3.3. Descriptive Statistics

Table I presents the descriptive statistics for the whole sample. I lose the years 1986 to 1990 of my data due to the definition of the variable *RatingDc* and because there was no rating discontinuity in 1990. For the same reason I exclude 2015 and 2016 due to missing observations for *RatingDc,* resulting in the period from 1991 to 2014 that is available for my analysis. For this period, the *DebtToEquityIssuance* averages 1.9%, *BookLev* at 35.3%, *MktLev* at 31.0%, *NetDebtIssuance* at 1.7%, and the average *Cash/Assets* ratio is 9.2% (see Table I). The summary statistics for the control variables align with the existing literature.

Table I: Descriptive Statistics - Full Sample

This table presents the descriptive statistics for the whole sample. *DebtToEquityIssuance i*s long-term debt issuance minus long-term debt reduction plus changes in current debt minus the sale of common and preferred stock minus the purchase of common and preferred stock divided by total assets. *BookLev* is long- and short-term debt divided by total assets, *MktLev* is total interest-bearing debt divided by the sum of total interest-bearing debt and market equity*, NetDebtIssuance* is defined as long-term debt issues minus long-term debt reductions minus current debt changes divided by total assets and *Cash/Assets* is cash and marketable securities divided by total assets. *Rating* is the domestic long-term issuer credit rating from S&P, converted into a numerical scale where each number represents one notch. *MarketToBook* is the ratio of the book value of assets plus the market value of equity minus the book value of common equity minus balance sheet deferred taxes to the book value of assets. *PPE/Assets* is the net property, plant, and equipment divided by total assets. *Profit* is EBITDA divided by sales. *Size* is the log of the book value of assets in constant 2005 dollars. *Carryfwd/Asset* is computed as tax loss carryforwards divided by total assets. *R&D/Sales* is the ratio of R&D expenditures to total sales. *CAPEX/Sales* is capital expenditures divided by sales. *Acq/Sales* is cash acquisitions divided by sales. *NWC/Assets* is net working capital less cash divided by assets. *Vol* is the profitability volatility, which is computed as rolling volatility over the current period and four previous periods. *DivDummy* is a dummy variable that takes one for years in which a firm pays a common dividend, zero otherwise. All variables are winsorized at the 95th percentile to account for outliers within the sample. *DebtToEquityIssuance*, *MarketToBook*, *NWC/Assets*, *Profit*, and *Vol*, are also winsorized at the 5th percentile.

[1] Volatility is computed using the current year's profit as well as the profit from the four previous years. Profit is defined as EBITDA divided by Sales. At least two years of data are required for the computation.

	N	Mean	Std	Min	25%	50%	75%	Max
DebtToEquityIssuance	23,700	0.019	0.092	-0.159	-0.030	0.006	0.065	0.228
BookLev	26,735	0.353	0.201	0.000	0.208	0.328	0.477	0.791
MktLev	26,599	0.310	0.225	0.000	0.130	0.263	0.454	0.792
NetDebtIssuance	25,854	0.017	0.075	-0.112	-0.021	0.000	0.045	0.210
Cash/Assets	27,550	0.092	0.096	0.000	0.019	0.057	0.132	0.343
Rating	23,872	10.473	3.576	1.000	8.000	11.000	13.000	20.000
LastRating	27,192	10.804	3.617	1.000	8.000	11.000	14.000	21.000
MarketToBook	25,352	1.593	0.695	0.839	1.083	1.372	1.874	3.446
PPE/Assets	27,399	0.614	0.378	0.000	0.296	0.560	0.897	1.371
Profit	27,506	0.174	0.122	0.007	0.085	0.144	0.236	0.466
Size	27,555	7.771	1.457	5.323	6.673	7.672	8.813	10.563
Carryfwd/Asset	27,555	0.056	0.112	0.000	0.000	0.000	0.048	0.418
R&D/Sales	27,555	0.020	0.040	0.000	0.000	0.000	0.019	0.146
CAPEX/Sales	27,555	0.095	0.124	0.000	0.025	0.046	0.100	0.498
Acq./Sales	25,656	0.032	0.067	0.000	0.000	0.000	0.024	0.257
NWC/Assets	26,302	0.035	0.124	-0.187	-0.051	0.021	0.117	0.285
Vol	25,460	0.035	0.038	0.004	0.011	0.021	0.042	0.150
Div. Dummy	27,555	0.397	0.489	0.000	0.000	0.000	1.000	1.000

Table II shows the distribution of the variable *RatingDc* over time, including 27,555 firm-year observations. For 2,469 observations, this dummy variable equals one, representing 9% of the whole sample. It is important to note that we do not see a jump in the number of firms with discontinuity over time. We can also observe that the average number of years that firms are unrated increases over time which implies that those firms remain in the sample. In total, the sample includes 2,741 firms.

Table II: Firms with Discontinued Ratings over Time

This table shows the distribution of observations over time. *Rated* shows the number of firms rated for at least three years in that respective year. *Disc* shows the number of firms that used to be rated for three years and discontinued their rating for at least one year. The column *Avg. YearsUnrated per Year* contains the average number of unrated years for firms with rating discontinuity for each year. The column *Disc. in % of Total* shows the proportion of observations where a firm used to be rated but is not rated anymore.

Year	*Rated*	*Disc*	*Observations per Year*	*Avg. YearsUnrated per Year*	*Disc in % of Total per year*
1991	670	49	719	2.551	0.068
1992	719	59	778	3.153	0.076
1993	841	61	902	3.705	0.068
1994	842	108	950	3.389	0.114
1995	907	116	1,023	4.000	0.113
1996	1,018	114	1,132	4.693	0.101
1997	1,116	92	1,208	5.522	0.076

1998	1,230	84	1,314	6.000	0.064
1999	1,205	103	1,308	5.408	0.079
2000	1,198	86	1,284	6.314	0.067
2001	1,180	77	1,257	6.948	0.061
2002	1,188	79	1,267	7.228	0.062
2003	1,202	97	1,299	6.619	0.075
2004	1,208	103	1,311	6.612	0.079
2005	1,167	115	1,282	6.600	0.090
2006	1,145	125	1,270	6.760	0.098
2007	1,071	122	1,193	7.230	0.102
2008	1,036	128	1,164	7.344	0.110
2009	1,002	129	1,131	7.543	0.114
2010	986	141	1,127	7.567	0.125
2011	995	126	1,121	7.873	0.112
2012	1,019	120	1,139	8.317	0.105
2013	1,042	118	1,160	8.508	0.102
2014	1,099	117	1,216	8.615	0.096
Total	25,086	2,469	27,555	6.187	0.090

I expect that firms with rating discontinuity issue on average less debt, have lower leverage, and hold higher amounts of cash since market access to debt is limited and more costly. Table III compares the summary statistics for continuously rated firm-years (*RatingDc* = 0) and observations with firms rated at least three years and discontinued their rating for at least one year (*RatingDc* = 1) for all three dependent variables. Continuously rated firms show, on average, 2.0% *DebtToEquityIssuance*, the average for firms that discontinued their ratings is significantly lower at 0.8%. Further, we can also observe that firms that dropped out of the rated bond market have a 10.1 percentage points lower book leverage and an 8.9 percentage points lower market leverage than firms continuously rated, averaging 36.2% and 31.8%, respectively. The average *NetDebtIssuance* for continuously rated firms is 1.8%, whereas the average for firms with rating discontinuity is 0.2%. On the contrary, the average ratio of cash and marketable securities to total assets for these firms is 13.2%, more than four percentage points higher than for continuously rated firms.

Table III: Dependent Variables - Rated Firms vs. Firms with Rating Discontinuity

This table contains the five dependent variables. It compares summary statistics for continuously rated firm-years (rated) and observations with firms rated for at least three years and discontinued their rating for at least one year. *Rated* includes firm-year observations where a firm was rated for at least three years (RatingDc = 0). *Disc* includes observations where firms used to be rated for three years and discontinued their rating for at least one year (RatingDc = 1). Variable definitions can be found in Table I.

	DebtToEquity Issuance		*BookLev*		*MktLev*		*NetDebt Issuance*		*Cash/Assets*	
	Rated	*Disc*	*Rated*	*Disc*	*Rated*	*Disc*	*Rated*	*Disc*	*Rated*	*Disc*
N	21,536	2,164	24,332	2,403	24,207	2,392	23,547	2,307	25,081	2,469
Mean	0.020	0.008	0.362	0.261	0.318	0.229	0.018	0.002	0.088	0.132
Std	0.092	0.090	0.196	0.229	0.223	0.233	0.076	0.067	0.092	0.118
Min	-0.159	-0.159	0.000	0.000	0.000	0.000	-0.112	-0.112	0.000	0.000
25%	-0.029	-0.036	0.221	0.060	0.140	0.026	-0.021	-0.025	0.019	0.028
50%	0.008	-0.001	0.336	0.218	0.271	0.158	0.000	0.000	0.054	0.092
75%	0.066	0.050	0.482	0.397	0.463	0.366	0.048	0.013	0.126	0.220
Max	0.228	0.228	0.791	0.791	0.792	0.792	0.210	0.210	0.343	0.343

In Table IV, I compare the control variables' mean, standard deviation, and median between the whole sample, continuously rated firm-years (*RatingDc* = 0), and observations where firms discontinued their ratings (*RatingDc* = 1). On one hand, firms with rating discontinuity have, on average, higher market-to-book ratios, higher *Carryforwards/Assets*, higher R&D spendings, higher net working capital, higher profit volatility, and pay more dividends. On the other hand, they have significantly lower last available ratings, fewer tangible assets, lower profits, are smaller, and have fewer investments and cash acquisitions.

Table IV: Control Variables - Rated Firms vs. Firms with Rating Discontinuity

This table compares the mean, standard deviation, and median of the control variables between the continuously rated firm-years (Rated) and observations where firms discontinued their ratings (Disc). Variable definitions are shown in Table I.

	Mean		Std		Median	
	Rated	*Disc*	*Rated*	*Disc*	*Rated*	*Disc*
LastRating	12.982	10.603	2.953	3.607	14.000	11.000
MarketToBook	1.645	1.588	0.743	0.690	1.396	1.370
PPE/Assets	0.579	0.618	0.362	0.379	0.505	0.567
Profit	0.142	0.177	0.118	0.122	0.114	0.148
Size	6.631	7.884	1.191	1.432	6.468	7.781
Carryfwd/Asset	0.089	0.053	0.149	0.107	0.000	0.000
R&D/Sales	0.031	0.019	0.051	0.038	0.000	0.000
CAPEX/Sales	0.066	0.098	0.093	0.126	0.035	0.047
Acq/Sales	0.023	0.033	0.057	0.068	0.000	0.000
NWC/Assets	0.068	0.031	0.144	0.121	0.065	0.019
Vol	0.049	0.034	0.046	0.036	0.030	0.020
Div. Dummy	0.543	0.382	0.498	0.486	1.000	0.000

4. Results

I test the impact of rating discontinuity on firms' capital structure decisions using debt-to-equity issuance, leverage, net debt issuance and cash holdings as dependent variables. I estimate three models over the period 1991 to 2014.

4.1. Changes in Debt-to-Equity Issuance

Table V presents the regression results for the *DebtToEquityIssuance* variable. In Panel A, I assess the relationship between *DebtToEquityIssuance* and *RatingDc*, together with a set of control variables lagged by one year. I examine if firms with rating discontinuity issue more or less debt in relation to equity as a fraction of total assets. The results show that the coefficients of *RatingDc* are significant at the 1% significance level in all regressions. Thus, holding everything else constant, firms with rating discontinuity issue 1.2 to 1.9 percentage points less debt in relation to equity as a fraction of total assets than continuously rated firms. Since the average for rated firms is 2.0% of total assets, this shows a drastic decrease in debt-to-equity issuance for the years after a firm discontinued its rating. The results seem to suggest that if the S&P rating had been replaced by a rating from another CRA, there should be no decline in *DebtToEquityIssuance*. However, this interpretation assumes that ratings from other CRAs like for example Moody's or Fitch are perfect substitutes for S&P ratings. Regarding the control variables, the results show that firms present higher *DebtToEquityIssuance* when they have lower book leverage, PPE/Asset ratios, R&D expenses, higher market-to-book ratios, profitability, and when they are smaller. These findings are in line with existing literature.

Panel B of Table V contains the regression results of the relationship between *DebtToEquityIssuance* and *YearsUnrated*, along with the same control variables as in Panel A (which I do not report for brevity and clarity). I use *YearsUnrated* to capture the effect of time after a firm decided to discontinue its rating on the debt-to-equity issuance. The coefficients of *YearsUnrated* for regressions (2), (3), and (5) to (7) are significant at the 1% significance level. For regressions (1) and (4), they are significant at the 5% and 10% significance level, respectively. All coefficients have negative signs, which confirms my prior results. Holding everything else constant, firms issue 0.1 to 0.2 percentage points less debt in relation to equity as a fraction of total assets with every additional year being unrated. This suggests that the effect on *DebtToEquityIssuance* does not occur immediately after firms become unrated but strengthens over time. The results for the control variables are consistent with the outcomes in Panel A of Table V.

Panel C of Table V presents the regression results of the relationship between *DebtToEquityIssuance* and *YearsRated*. I use *YearsRated* to capture a potential reputation effect. A higher value of *YearsRated* implies a longer rating history for a firm. Thus, it might be perceived as more reliable. Based on this, I expect firms to have higher *DebtToEquityIssuance,* with every year being rated. The coefficients of *YearsRated* for regressions (3) and (7) are significant at the 1% significance level. For regressions (6), they are significant at the 5% significance level. For regressions (2) and (4), they are significant at the 10% significance level, and for regressions (1) and (5) they are not significant. The coefficients for *YearsRated* are zero in all regressions. This implies that a longer rating history has no impact on *DebtToEquityIssuance.* The results for the control variables are consistent with the prior outcomes.

Table V: Regression Results – *DebtToEquityIssuance*

This table is divided into three panels. Panel A shows the coefficients for the regressions of changes in *DebtToEquityIssuance* with *RatingDc* as the key explanatory variable. Panel B shows the coefficients for the regressions with *YearsUnrated*, and Panel C the coefficients for *YearsRated* as the key explanatory variables. In Panels B and C, I use the same control variables as in Panel A, but I do not report them for brevity and clarity. All columns represent OLS regressions. Results in column (3) include Year FE. Column (4) includes Firm FE. Column (5) includes both Year and Firm FE. Column (6) includes Industry FE, and column (7) Year and Industry FE. L1. denotes the lag operator. Variable definitions can be found in Table I. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

	Panel A: Impact of *RatingDc*						
	DebtToEquityIssuance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.*RatingDc*	-0.012	-0.018	-0.017	-0.013	-0.015	-0.018	-0.019
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.*BookLev*		-0.071	-0.070	-0.165	-0.163	-0.076	-0.075
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.*MarketToBook*		0.022	0.020	0.023	0.019	0.022	0.019
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.*(PPE/Assets)*		-0.010	-0.008	0.006	0.007	-0.009	-0.007
		(<0.01)	(<0.01)	(0.15)	(0.11)	(<0.01)	(<0.01)
L1.*Profit*		0.063	0.054	0.059	0.052	0.067	0.059
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.*Size*		-0.000	-0.001	-0.003	-0.003	-0.000	-0.001
		(0.85)	(0.36)	(<0.01)	(0.01)	(0.82)	(0.31)
L1.*(Carryfwd/Assets)*		-0.011	-0.019	0.002	-0.001	-0.007	-0.015
		(0.11)	(<0.01)	(0.81)	(0.92)	(0.35)	(0.03)
L1.*(R&D/Sales)*		-0.192	-0.162	-0.220	-0.189	-0.170	-0.139

		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	23,700	21,124	21,124	21,124	21,124	21,124	21,124
Number of Firms	2,682	2,655	2,655	2,655	2,655	2,655	2,655
Adjusted R^2	0.000	0.064	0.099	0.087	0.118	0.068	0.103

Panel B: Impact of *YearsUnrated*

	DebtToEquityIssuance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.*YearsUnrated*	-0.001	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002
	(0.04)	(<0.01)	(<0.01)	(0.09)	(<0.01)	(<0.01)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	23,700	21,124	21,124	21,124	21,124	21,124	21,124
Number of Firms	2,682	2,655	2,655	2,655	2,655	2,655	2,655
Adjusted R^2	0.000	0.064	0.099	0.088	0.118	0.068	0.103

Panel C: Impact of *YearsUnrated*

	DebtToEquityIssuance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.*YearsRated*	0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.11)	(0.07)	(<0.01)	(0.08)	(0.34)	(0.03)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	23,700	21,124	21,124	21,124	21,124	21,124	21,124
Number of Firms	2,682	2,655	2,655	2,655	2,655	2,655	2,655
Adjusted R^2	0.001	0.064	0.099	0.090	0.122	0.068	0.103

Next, I perform robustness tests for my *DebtToEquityIssuance* regressions by adding the two variables *LastRating* and *LastInvGrade* to the models. The results can be found in Table VI. The *LastRating* variable represents the last available credit rating from S&P received by a firm, while a value of 1 is equivalent to an AAA rating and 21 is equal to C. *LastInvGrade* is a dummy variable based on *LastRating* and takes one if the respective firm was last rated as investment grade and zero otherwise. I select two regressions of each model with the highest explanatory power (highest adjusted R^2) from my *DebtToEquityIssuance* regressions. Panel A of Table VI shows the results with the *LastRating* variable added to the models while keeping everything else unchanged. The coefficients of *LastRating* are significant at the 1% significance level for all regressions. The hypothesis is that firms with lower ratings are perceived as riskier and should have lower *DebtToEquityIssuance.* The outcomes suggest that, keeping everything else constant, a rating decrease of one notch results in a 0.1 to 0.5 percentage points reduction of *DebtToEquityIssuance*. Further, adding *LastRating* to my models has no impact on the significance of my explanatory variables and only a little impact on the coefficients. Rating discontinuity and the number of unrated years still negatively impact *DebtToEquityIssuance.* The results in Panel B of Table VI confirm this interpretation. The coefficients for *LastInvGrade* are significant at the 1% significance level for all regressions, thus firms being formerly rated 'investment grade' have on average 0.6 to 1.8 percentage points higher *DebtToEquityIssuance*. Adding *LastInvGrade* to my models has no impact on the significance of the explanatory variables and only a little impact on the coefficients.

Table VI: *DebtToEquityIssuance* Robustness

This table is divided into two panels. Panel A reports the results for the DebtToEquityIssuance regressions with LastRating added to the models. Panel B shows the regression results with LastInvGrade added to the models. All columns represent OLS regressions. Results in columns (1), (3), and (5) include Year and Firm FE. Columns (2), (4), and (6) include Year and Industry FE. I use the same control variables as in Table V, but I do not report them for brevity and clarity. L1. denotes the lag operator. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

Panel A: *LastRating* added to the models						
	DebtToEquityIssuance					
	(1)	(2)	(3)	(4)	(5)	(6)
L1.*RatingDc*	-0.013	-0.017				
	(<0.01)	(<0.01)				
L1.*YearsUnrated*			-0.001	-0.002		
			(<0.01)	(<0.01)		
L1.*YearsRated*					0.000	-0.001
					(0.83)	(<0.01)
LastRating	-0.004	-0.001	-0.004	-0.001	-0.005	-0.001
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	21,124	21,124	21,124	21,124	21,124	21,124
Number of Firms	2,655	2,655	2,655	2,655	2,655	2,655
Adjusted R^2	0.124	0.106	0.123	0.106	0.123	0.105

	Panel B: *LastInvGrade* added to the models					
	DebtToEquityIssuance					
	(1)	(2)	(3)	(4)	(5)	(6)
L1.*RatingDc*	-0.013	-0.018				
	(<0.01)	(<0.01)				
L1.*YearsUnrated*			-0.001	-0.002		
			(0.01)	(<0.01)		
L1.*YearsRated*					-0.000	-0.000
					(0.59)	(<0.01)
LastInvGrade	0.018	0.006	0.018	0.006	0.018	0.009
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	21,124	21,124	21,124	21,124	21,124	21,124
Number of Firms	2,655	2,655	2,655	2,655	2,655	2,655
Adjusted R^2	0.123	0.104	0.123	0.104	0.128	0.104

4.2. Changes in Leverage

Table VII presents the regression results for the *BookLev* variable. In panel A, I assess the relationship between *BookLev* and *RatingDc* and a set of control variables. I examine whether firms with rating discontinuity present higher or lower book leverage than continuously rated firms. The results show that the coefficients of *RatingDc* are significant at the 1% significance level in all regressions. Thus, holding everything else constant, firms with rating discontinuity have 8.1 to 13.3 percentage points lower *BookLev* than continuously rated firms. Considering the average *BookLev* for rated firms is 36.2%, this shows a drastic decrease in the years after a firm discontinued its rating. The results also confirm my prior finding that we observe actual rating discontinuity, considering that if the S&P rating had been replaced by a rating from another CRA, there should be no decline in *BookLev*. However, this interpretation assumes again that ratings from other CRAs like for example Moody's or Fitch are perfect substitutes for S&P ratings. Regarding the control variables, the results show that firms issue more debt when they have lower market-to-book ratios, higher PPE/Asset ratios, lower R&D expenses, and when they are smaller.

Panel B of Table VII contains the regression results of the relationship between *BookLev* and *YearsUnrated*, along with the same set of control variables as in Panel A. I use *YearsUnrated* to capture the effect of time after a firm decided to discontinue its rating on

BookLev. The coefficients of *YearsUnrated* are significant at the 1% significance level in all regressions and all coefficients have negative signs, which confirms my prior results. Holding everything else constant, firms present 1.0 to 1.5 percentage points lower *BookLev,* with every additional year being unrated. This suggests that the effect on *BookLev* does not occur immediately after firms become unrated but strengthens over time. The results for the control variables are consistent with the first model.

Panel C of Table VII presents the regression results of the relationship between *BookLev* and *YearsRated*. A higher value for the coefficient of *YearsRated* implies a longer rating history for a firm. Thus, it might be perceived as more reliable. Based on this, I would expect firms to have higher *BookLev* with every year being rated. The coefficients of *YearsRated* are only significant at the 1% significance level for regressions (1) and (5) and at the 10% significance level for regressions (2). However, the coefficients are very small and have different signs, which is contradicting. Thus, there is no evidence of a reputation effect for *BookLev*. The results for the control variables are consistent with the first model.

Table VII: Regression Results – *BookLev*

This table is divided into three panels. Panel A shows the coefficients for the regressions of changes in *BookLev* with *RatingDc* as the key explanatory variable. Panel B shows the coefficients for the regressions with *YearsUnrated*, and Panel C the coefficients for *YearsRated* as the key explanatory variables. In Panels B and C, I use the same control variables as in Panel A, but I do not report them for brevity and clarity. All columns represent OLS regressions. Results in column (3) include Year FE. Column (4) includes Firm FE. Column (5) includes both Year and Firm FE. Column (6) includes Industry FE, and column (7) Year and Industry FE. Variable definitions can be found in Table I. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

	Panel A: Impact of *RatingDc*						
	BookLev						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RatingDc	-0.101	-0.133	-0.131	-0.090	-0.081	-0.131	-0.129
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
MarketToBook		-0.025	-0.025	-0.018	-0.015	-0.026	-0.026
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
PPE/Assets		0.009	0.009	0.049	0.055	0.016	0.018
		(0.35)	(0.31)	(<0.01)	(<0.01)	(0.12)	(0.08)
Profit		0.198	0.199	-0.116	-0.111	0.136	0.139
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Size		-0.035	-0.035	-0.010	0.000	-0.035	-0.035
		(<0.01)	(<0.01)	(<0.01)	(1.00)	(<0.01)	(<0.01)
Carryfwd/Asset		0.246	0.255	0.076	0.111	0.227	0.232

		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
R&D/Sales		-0.908	-0.900	-0.214	-0.215	-0.737	-0.730
		(<0.01)	(<0.01)	(0.35)	(0.35)	(<0.01)	(<0.01)
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	26,734	24,483	24,483	24,483	24,483	24,483	24,483
Number of Firms	2,740	2,690	2,690	2,690	2,690	2,690	2,690
Adjusted R^2	0.015	0.148	0.163	0.031	0.061	0.193	0.207

Panel B: Impact of *YearsUnrated*

	BookLev						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
YearsUnrated	-0.012	-0.015	-0.015	-0.011	-0.010	-0.014	-0.014
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	26,735	24,483	24,483	24,483	24,483	24,483	24,483
Number of Firms	2,740	2,690	2,690	2,690	2,690	2,690	2,690
Adjusted R^2	0.021	0.151	0.165	0.043	0.070	0.197	0.210

Panel C: Impact of *YearsRated*

	BookLev						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
YearsRated	-0.003	-0.001	-0.000	-0.001	0.004	-0.000	-0.000
	(<0.01)	(0.10)	(0.41)	(0.28)	(<0.01)	(0.45)	(0.93)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	26,735	24,484	24,484	24,484	24,484	24,484	24,484
Number of Firms	2,740	2,690	2,690	2,690	2,690	2,690	2,690
Adjusted R^2	0.012	0.124	0.139	0.019	0.057	0.170	0.184

Next, I perform robustness tests for my *BookLev* regressions by adding the two variables *LastRating* and *LastInvGrade* to the models. The results can be found in Table VIII. The *LastRating* variable represents the last available credit rating from S&P received by a firm, while a value of 1 is equivalent to an AAA rating and 21 is equal to C. *LastInvGrade* is a dummy variable based on *LastRating* and takes one if the respective firm was last rated as investment grade and zero otherwise. I select two regressions of each model with the highest explanatory power (highest adjusted R^2) from my *BookLev* regressions. Panel A shows the results with the *LastRating* variable added to the models while keeping everything else unchanged. The coefficients of *LastRating* are significant at the 1% significance level for all regressions. The outcome suggests that keeping everything else constant, for a one-notch downgrade *BookLev* increases by 2.7 to 2.8 percentage points. Further, adding *LastRating* to my models has no impact on the significance of *RatingDc* and *YearsUnrated* and only a little impact on the coefficients. Rating discontinuity and the number of unrated years still negatively impact *BookLev*. Surprisingly, the coefficients for *YearsRated* are now significant at the 1% significance level. Thus, with every additional year being rated, the *BookLev* increases by 0.1 percentage points which suggests that there might be a reputational effect on the *BookLev* of firms. This can also be explained by a reputation effect and more available historical data. The results in Panel B confirm this interpretation. The coefficients for *LastInvGrade* are significant at the 1% significance level for all regressions, thus firms being formerly rated 'investment grade' have 12.3 to 13.0 percentage points lower *BookLev,* which is a large effect. The coefficients for *YearsRated* are now also significant at the 1% and 5% significance level respectively, suggesting a 0.1 percentage point increase in *BookLev* with every year being rated. Adding *LastInvGrade* to my models has no impact on the significance of explanatory variables and only a little impact on the coefficients.

Table VIII: *BookLev* Robustness

This table is divided into two panels. Panel A reports the results for the *BookLev* regressions with *LastRating* added to the models. Panel B shows the regression results with *LastInvGrade* added to the models. All columns represent OLS regressions. Results in columns (1), (3), and (5) include Year FE. Columns (2), (4), and (6) include Year and Industry FE. I use the same control variables as in Panel A of Table VII, but I do not report them for brevity and clarity. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

Panel A: *LastRating* added to the models						
	BookLev					
	(1)	(2)	(3)	(4)	(5)	(6)
RatingDc	-0.132	-0.131				
	(<0.01)	(<0.01)				
YearsUnrated			-0.014	-0.014		
			(<0.01)	(<0.01)		
YearsRated					0.001	0.001
					(<0.01)	(<0.01)
LastRating	0.027	0.027	0.027	0.027	0.028	0.028

	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	24,156	24,156	24,156	24,156	24,156	24,156
Number of Firms	2,686	2,686	2,686	2,686	2,686	2,686
Adjusted R^2	0.278	0.315	0.272	0.310	0.250	0.288

Panel B: *LastInvGrade* added to the models

	BookLev					
	(1)	(2)	(3)	(4)	(5)	(6)
RatingDc	-0.137	-0.135				
	(<0.01)	(<0.01)				
YearsUnrated			-0.015	-0.015		
			(<0.01)	(<0.01)		
YearsRated					0.001	0.001
					(0.02)	(<0.01)
LastInvGrade	-0.129	-0.125	-0.127	-0.123	-0.130	-0.125
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	24,483	24,483	24,483	24,483	24,483	24,483
Number of Firms	2,690	2,690	2,690	2,690	2,690	2,690
Adjusted R^2	0.226	0.265	0.223	0.262	0.192	0.233

To confirm the results for *BookLev,* I also test the impact on the *MktLev* variable. The results are presented in Table IX Overall, the outcomes are very similar to my *BookLev* regressions. In Panel A, I assess the relationship between *MktLev* and *RatingDc.* I use the same control variables as before but do not report them for brevity and clarity. The results show that the coefficients of *RatingDc* are significant at the 1% significance level in all regressions. Thus, holding everything else constant, firms with rating discontinuity have 7.2 to 11.6 percentage points lower *MktLev* than continuously rated firms. Considering the average *MktLev* for rated firms is 31.8%, this shows a drastic decrease in the years after a firm discontinued its rating. Assuming that ratings from other CRAs are perceived by investors as perfect substitutes, the results confirm my prior finding that we observe actual rating discontinuity and that there is no evidence for issuer shopping in the sample. Otherwise, we should not have seen a reduction in

MktLev. Regarding the control variables, the results are broadly in line with the *BookLev* regressions.

Panel B of Table IX contains the regression results of the relationship between *MktLev* and *YearsUnrated*. The coefficients of *YearsUnrated* are significant at the 1% significance level in all regressions. Holding everything else constant, firms present 0.8 to 1.3 percentage points lower *MktLev* with every additional year being unrated. This suggests that the effect on *MktLev* does not occur immediately after firms become unrated but strengthens over time.

Panel C of Table IX presents the regression results of the relationship between *MktLev* and *YearsRated*. I use *YearsRated* to capture a potential reputation effect. A higher value for the coefficient of *YearsRated* implies a longer rating history for a firm. Thus, it might be perceived as more reliable. Based on this, I would expect firms to have higher *MktLev* with every year being rated. The coefficients of *YearsRated* are only significant at the 1% significance level for regressions (1) and (5) and at the 10% significance level for regressions (2). Again, the coefficients are very small and for regressions (4) and (5) they have different signs, which is contradictory. Thus, there is no evidence of a reputation effect for *MktLev*. The results for the control variables are consistent with the first model.

Table IX: Regression Results – *MktLev*

This table is divided into three panels. Panel A shows the coefficients for the regressions of changes in *MktLev* with *RatingDc* as the key explanatory variable. Panel B shows the coefficients for the regressions with *YearsUnrated*, and Panel C the coefficients for *YearsRated* as the key explanatory variables. In Panels B and C, I use the same control variables as in Panel A, but I do not report them for brevity and clarity. All columns represent OLS regressions. Results in column (3) include Year FE. Column (4) includes Firm FE. Column (5) includes both Year and Firm FE. Column (6) includes Industry FE, and column (7) Year and Industry FE. Variable definitions can be found in Table I. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

Panel A: Impact of *RatingDc*							
	MktLev						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RatingDc	-0.089	-0.116	-0.113	-0.083	-0.072	-0.113	-0.111
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	26,598	24,483	24,483	24,483	24,483	24,483	24,483
Number of Firms	2,732	2,690	2,690	2,690	2,690	2,690	2,690

Adjusted R^2	0.013	0.404	0.419	0.291	0.326	0.429	0.442

Panel B: Impact of *YearsUnrated*

	MktLev						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
YearsUnrated	-0.011	-0.013	-0.013	-0.010	-0.008	-0.013	-0.012
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	26,599	24,484	24,484	24,484	24,484	24,484	24,484
Number of Firms	2,732	2,690	2,690	2,690	2,690	2,690	2,690
Adjusted R^2	0.017	0.405	0.419	0.289	0.325	0.428	0.442

Panel C: Impact of *YearsRated*

	MktLev						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
YearsRated	-0.003	-0.001	-0.000	-0.001	0.003	-0.000	-0.000
	(<0.01)	(0.10)	(0.51)	(0.02)	(<0.01)	(0.35)	(0.96)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	26,599	24,484	24,484	24,484	24,484	24,484	24,484
Number of Firms	2,732	2,690	2,690	2,690	2,690	2,690	2,690
Adjusted R^2	0.008	0.385	0.400	0.277	0.318	0.410	0.425

When performing the robustness tests for the *MktLev* regressions I come to the very same conclusions as for my *BookLev* regressions. The results can be found in Table X. Panel A shows the results with the *LastRating* variable added to the models while keeping everything else unchanged. The coefficients of *LastRating* are also significant at the 1% significance level for all regressions. The outcome shows that, keeping everything else constant, *MktLev* increases by 3.0 to 3.1 percentage points for a rating decrease of one notch. Further, adding *LastRating* to my models has no impact on the significance of *RatingDc* and *YearsUnrated* and only a little impact on the coefficients. Rating discontinuity and the number of unrated years still negatively impact *MktLev*. And as for *BookLev*, the coefficients for *YearsRated* are now significant at the 1% significance level. Thus, with every additional year being rated, the *MktLev* increases by 0.2 percentage points which suggests that there might be a reputational effect on the *MktLev* of firms. The results in Panel B of Table X confirm this finding. The coefficients for *LastInvGrade* are significant at the 1% significance level for all regressions, thus firms being formerly rated 'investment grade' have 14.3 to 15.0 percentage points lower *MktLev,* which is a large effect. The coefficients for *YearsRated* are now also significant at the 1% level, suggesting a 0.2 percentage point increase in *MktLev* with every year being rated. Adding *LastInvGrade* to my models has no impact on the significance of *RatingDc* and *YearsUnrated* and had only a little impact on their coefficients.

Table X: *MktLev* Robustness

This table is divided into two panels. Panel A reports the results for the *MktLev* regressions with *LastRating* added to the models. Panel B shows the regression results with *LastInvGrade* added to the models. All columns represent OLS regressions. Results in columns (1), (3), and (5) include Year FE. Columns (2), (4), and (6) include Year and Industry FE. I use the same control variables as in Panel A of Table VII, but I do not report them for brevity and clarity. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

Panel A: *LastRating* added to the models						
	MktLev					
	(1)	(2)	(3)	(4)	(5)	(6)
RatingDc	-0.113	-0.111				
	(<0.01)	(<0.01)				
YearsUnrated			-0.012	-0.012		
			(<0.01)	(<0.01)		
YearsRated					0.002	0.002
					(<0.01)	(<0.01)
LastRating	0.030	0.030	0.030	0.030	0.031	0.031
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	24,156	24,156	24,156	24,156	24,156	24,156
Number of Firms	2,686	2,686	2,686	2,686	2,686	2,686
Adjusted R^2	0.519	0.538	0.521	0.540	0.510	0.529

Panel B: *LastInvGrade* added to the models						
	MktLev					
	(1)	(2)	(3)	(4)	(5)	(6)
RatingDc	-0.119	-0.117				
	(<0.01)	(<0.01)				
YearsUnrated			-0.013	-0.013		

			(<0.01)	(<0.01)		
YearsRated					0.002	0.002
					(<0.01)	(<0.01)
LastInvGrade	-0.148	-0.145	-0.146	-0.143	-0.150	-0.146
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	24,483	24,483	24,483	24,483	24,483	24,483
Number of Firms	2,690	2,690	2,690	2,690	2,690	2,690
Adjusted R^2	0.479	0.498	0.478	0.497	0.459	0.480

I further test the impact on *NetDebtIssuance.* The results are presented in Table XI. Overall, the outcomes are strongly in line with the *BookLev* and regressions *MktLev*. The results in Panel A show that the coefficients of *RatingDc* are significant at the 1% significance level in all regressions. Thus, holding everything else constant, firms with rating discontinuity present 1.6 to 2.2 percentage points lower *NetDebtIssuance* than continuously rated firms. Considering the average *NetDebtIssuance* for rated firms is 1.8%, this also shows a drastic decrease in the years after a firm discontinued its rating. As shown in the previous results, and assuming that ratings from other CRAs are perfect substitutes, a potential explanation is that we observe actual rating discontinuity and that there is no evidence for issuer shopping. Regarding the control variables, the results are in line with the *DebtToEquityIssuance* regressions. The coefficients of *YearsUnrated* are significant at the 1% significance level in all regressions (see Panel B). Holding everything else constant, firms present 0.1 to 0.2 percentage points lower *NetDebtIssuance,* with every additional year being unrated. This suggests that the effect on *NetDebtIssuance* does not occur immediately after firms become unrated.

Panel C from Table XI presents the regression results of the relationship between *MktLev* and *YearsRated* to capture a potential reputation effect. The coefficients of *YearsRated* are significant at the 1% significance level for all regressions. Holding everything else constant, firms present 0.1 to 0.2 percentage points lower *NetDebtIssuance.* This confirms my expectation that lenders and investors may perceive firms with long-standing ratings as lower-risk borrowers, which could result in easier access to capital and reduce the need for new debt issuance. The results for the control variables are consistent with the first model.

Table XI: Regression Results – *NetDebtIssuance*

This table is divided into three panels. Panel A shows the coefficients for the regressions of changes in *NetDebtIssuance* with *RatingDc* as the key explanatory variable. Panel B shows the coefficients for the regressions with *YearsUnrated*, and Panel C the coefficients for *YearsRated* as the key explanatory variables. In Panels B and C, I use the same control variables as in Panel A, but I do not report them for brevity and clarity. All columns represent OLS regressions. Results in column (3) include Year FE. Column (4) includes Firm FE. Column (5) includes both Year and Firm FE. Column (6) includes Industry FE, and column (7) Year and Industry FE. L1. denotes the lag operator. Variable definitions can be found in Table I. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

	Panel A: Impact of *RatingDc*						
	NetDebtIssuance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.*RatingDc*	-0.016	-0.022	-0.022	-0.020	-0.016	-0.022	-0.021
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.*BookLev*		-0.023	-0.024	-0.103	-0.104	-0.026	-0.027
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.*MarketToBook*		0.011	0.009	0.015	0.013	0.012	0.010
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.(*PPE/Assets)*		-0.003	-0.003	0.008	0.008	-0.007	-0.007
		(0.06)	(0.07)	(0.03)	(0.02)	(<0.01)	(<0.01)
L1.*Profit*		0.052	0.050	0.032	0.024	0.029	0.027
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
L1.*Size*		-0.004	-0.003	-0.006	-0.003	-0.003	-0.003
		(<0.01)	(<0.01)	(<0.01)	(0.01)	(<0.01)	(<0.01)
L1.(*Carryfwd/Asset)*		0.004	0.007	-0.012	-0.000	0.001	0.005
		(0.44)	(0.20)	(0.09)	(0.97)	(0.84)	(0.43)
L1.*(R&D/Sales)*		-0.113	-0.098	-0.156	-0.144	-0.091	-0.076
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	25,854	23,067	23,067	23,067	23,067	23,067	23,067
Number of Firms	2,741	2,720	2,720	2,720	2,720	2,720	2,720
Adjusted R^2	0.000	0.023	0.050	0.056	0.080	0.030	0.057

	Panel B: Impact of *YearsUnrated*						
	NetDebtIssuance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.*YearsUnrated*	-0.001	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes

Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	25,854	23,067	23,067	23,067	23,067	23,067	23,067
Number of Firms	2,741	2,720	2,720	2,720	2,720	2,720	2,720
Adjusted R^2	0.001	0.022	0.049	0.056	0.080	0.029	0.056

Panel C: Impact of *YearsRated*

	NetDebtIssuance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.*YearsRated*	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	25,854	23,067	23,067	23,067	23,067	23,067	23,067
Number of Firms	2,741	2,720	2,720	2,720	2,720	2,720	2,720
Adjusted R^2	0.003	0.024	0.051	0.057	0.087	0.031	0.057

Next, I perform robustness tests for my *NetDebtIssuance* regressions by adding the two variables *LastRating* and *LastInvGrade* to the models. The results can be found in Table XII. Again, I select two regressions of each model with the highest explanatory power (highest adjusted R^2) from my *NetDebtIssuance* regressions. Panel A shows the results with the *LastRating* variable added to the models while keeping everything else unchanged. The coefficients of *LastRating* are significant at the 1% significance level for regressions (2), and (4) to (6) and significant at the 5% significance level for regressions (2) and (3). The hypothesis is that firms with lower ratings are perceived as riskier and should issue less debt. The outcome suggests that keeping everything else constant, for a rating decrease of one notch *NetDebtIssuance* decreases by 0.1 to 0.2 percentage points. Adding the rating information to my models impacts the sign for the coefficients of the *YearsRated* variable which is contradicting the previous results in Panel C of Table XII.

However, the results are in line with the outcomes form the *BookLev* and *MktLev* robustness test, suggesting a small increase in *NetDebtIssuance* the longer a firm has had a rating. One interpretation is that this indicates a small reputational effect through the stable delivery of rating information to the market. Further, adding *LastRating* to my models has no impact on the significance of my explanatory variables and only a little impact on the coefficients. *RatingDc* and *YearsUnrated* still negatively impact *NetDebtIssuance.* The results in Panel B of

Table XII confirm this finding. The coefficients for *LastInvGrade* are significant at the 1% significance level for all regressions, thus firms being formerly rated 'investment grade' have 0.7 to 1.0 percentage points lower *NetDebtIssuance,* which is a large effect. Adding *LastInvGrade* has no impact on the significance of the other variables and only a little impact on the coefficients. *RatingDc* and *YearsUnrated* still negatively impact *NetDebtIssuance.*

Table XII: *NetDebtIssuance* Robustness

This table is divided into two panels. Panel A reports the results for the *NetDebtIssuance* regressions with *LastRating* added to the models. Panel B shows the regression results with *LastInvGrade* added to the models. All columns represent OLS regressions. Results in columns (1), (3), and (5) include Year FE and Firm FE. Columns (2), (4), and (6) include Year and Industry FE. L1. denotes the lag operator. I use the same control variables as in Panel A of Table XI, but I do not report them for brevity and clarity. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

Panel A: *LastRating* added to the models						
	NetDebtIssuance					
	(1)	(2)	(3)	(4)	(5)	(6)
L1.*RatingDc*	-0.014	-0.021				
	(<0.01)	(<0.01)				
L1.*YearsUnrated*			-0.001	-0.002		
			(<0.01)	(<0.01)		
L1.*YearsRated*					0.001	0.001
					(0.02)	(<0.01)
LastRating	-0.001	-0.002	-0.001	-0.002	-0.002	-0.002
	(0.02)	(<0.01)	(0.04)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	22,764	22,764	22,764	22,764	22,764	22,764
Number of Firms	2,715	2,715	2,715	2,715	2,715	2,715
Adjusted R^2	0.082	0.065	0.081	0.062	0.081	0.069

Panel B: *LastInvGrade* added to the models						
	NetDebtIssuance					
	(1)	(2)	(3)	(4)	(5)	(6)
L1.*RatingDc*	-0.004	-0.008				
	(<0.01)	(<0.01)				
L1.*YearsUnrated*			-0.001	-0.002		
			(<0.01)	(<0.01)		
L1.*YearsRated*					0.001	0.001

					(<0.01)	(<0.01)
LastInvGrade	-0.007	-0.010	-0.007	-0.009	-0.009	-0.008
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	23,067	23,067	23,067	23,067	23,067	23,067
Number of Firms	2,720	2,720	2,720	2,720	2,720	2,720
Adjusted R^2	0.080	0.059	0.081	0.058	0.088	0.059

4.3. Changes in Cash Holdings

Last, I also test the impact of *RatingDc*, *YearsUnrated* and *YearsRated* on the *Cash/Assets* variable. The results are presented in Table XIII. In Panel A, I assess the relationship between *Cash/Assets* and *RatingDc.* The results show that the coefficients of *RatingDc* are significant at the 1% significance level in all regressions except for regression (5) where I employ Year FE and Firm FE. Thus, holding everything else constant, firms with rating discontinuity have 0.9 to 4.4 percentage points higher *Cash/Assets* ratios than continuously rated firms. Considering the average *Cash/Assets* ratio of the sample this shows a steep increase in the years after a firm discontinued its rating. The results confirm my prior findings which suggest that we observe actual rating discontinuity. If ratings from other CRAs are perceived as perfect substitutes, we should not have seen an increase in *Cash/Assets.* Regarding the control variables, the results show that firms have higher cash holdings when they have lower *Acq/Sales*, lower *CAPEX/Sales*, lower *NWC/Sales,* lower *PPE/Asset* ratios, lower profits, higher volatility in profitability, higher *MarketToBook* ratios, higher *Carryfwd/Asset*, higher R&D expenses, and when they pay a common dividend.

Panel B of Table XIII contains the regression results of the relationship between *Cash/Assets* and *YearsUnrated*. The coefficients of *YearsUnrated* are significant at the 1% significance level in all regressions except for regressions where I employ Firm FE. In regression (4), the coefficient of *RatingDc* is significant at the 5% level, and in regression (5) it is not significant. Holding everything else constant, firms present 0.1 to 0.6 percentage points lower *Cash/Assets* with every additional year being unrated. This suggests that the effect on *Cash/Assets* does not occur immediately after firms become unrated but strengthens over time.

Panel C of Table XIII presents the regression results of the relationship between *Cash/Assets* and *YearsRated*. I again use *YearsRated* to capture a potential reputation effect. A higher value of *YearsRated* implies a longer rating history for a firm. Thus, it might be perceived as a more reliable. Based on this, I would expect firms to have higher *Cash/Assets* ratios with every year being rated. The coefficients of *YearsRated* are only significant at the 1% significance level for regressions (1) and (4). For regressions (5) and (7), it is significant at the 5% and 10% significance level respectively. For the regressions (2), (3), and (6), the coefficients of *YearsRated* are not significant. Again, the coefficients are very small and for regressions (4) and (5) they have different signs, which is contradictory. Thus, there is no evidence for a reputation effect for *Cash/Assets*. The results for the control variables are consistent with the first model.

Table XIII: Regression Results – *Cash/Assets*

This table is divided into three panels. Panel A shows the coefficients for the regressions of changes in *Cash/Assets* with *RatingDc* as the key explanatory variable. Panel B shows the coefficients for the regressions with *YearsUnrated*, and Panel C the coefficients for *YearsRated* as the key explanatory variables. In Panels B and C, I use the same control variables as in Panel A, but I do not report them for brevity and clarity. All columns represent OLS regressions. Results in column (3) include Year FE. Column (4) includes Firm FE. Column (5) includes both Year and Firm FE. Column (6) includes Industry FE, and column (7) Year and Industry FE. Variable definitions can be found in Table I. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

	Panel A: Impact of *RatingDc*						
	Cash/Assets						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RatingDc	0.044	0.022	0.018	0.009	-0.000	0.021	0.017
	(<0.01)	(<0.01)	(<0.01)	(0.01)	(0.82)	(<0.01)	(<0.01)
Acq/Sales		-0.191	-0.179	-0.126	-0.100	-0.186	-0.173
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
DivDummy		0.012	0.009	0.002	0.001	0.011	0.008
		(<0.01)	(<0.01)	(0.55)	(0.80)	(<0.01)	(<0.01)
CAPEX/Sales		-0.018	-0.000	-0.076	-0.035	-0.012	0.010
		(0.12)	(0.97)	(<0.01)	(<0.01)	(0.31)	(0.42)
NWC/Assets		-0.131	-0.132	-0.166	-0.158	-0.135	-0.136
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Vol		0.395	0.374	0.196	0.181	0.405	0.389
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
MarketToBook		0.020	0.021	0.017	0.015	0.021	0.021
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
PPE/Assets		-0.046	-0.044	-0.077	-0.088	-0.044	-0.042
		(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Profit		-0.046	-0.063	0.016	0.019	-0.041	-0.058
		(<0.01)	(<0.01)	(0.21)	(0.14)	(<0.01)	(<0.01)
Size		-0.001	-0.005	-0.000	-0.018	-0.001	-0.005

		(0.21)	(<0.01)	(0.76)	(<0.01)	(0.22)	(<0.01)
Carryfwd/Asset		0.012	-0.016	0.027	-0.017	0.013	-0.015
		(0.23)	(0.11)	(<0.01)	(0.08)	(0.18)	(0.14)
R&D/Sales		0.832	0.849	0.299	0.252	0.780	0.792
		(<0.01)	(<0.01)	(<0.01)	(0.01)	(<0.01)	(<0.01)
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	27,549	20,786	20,786	20,786	20,786	20,786	20,786
Number of Firms	2,761	2,432	2,432	2,432	2,432	2,432	2,432
Adjusted R^2	0.017	0.357	0.376	0.107	0.155	0.370	0.389

Panel B: Impact of *YearsUnrated*

	Cash/Assets						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
YearsUnrated	0.006	0.003	0.002	0.001	-0.000	0.003	0.002
	(<0.01)	(<0.01)	(<0.01)	(0.03)	(0.45)	(<0.01)	(<0.01)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	27,550	20,787	20,787	20,787	20,787	20,787	20,787
Number of Firms	2,761	2,432	2,432	2,432	2,432	2,432	2,432
Adjusted R^2	0.021	0.358	0.376	0.108	0.155	0.370	0.388

Panel C: Impact of *YearsRated*

	Cash/Assets						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
YearsRated	-0.001	0.000	-0.000	0.003	-0.001	0.000	-0.000
	(<0.01)	(0.15)	(0.15)	(<0.01)	(0.02)	(0.19)	(0.08)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
Firm FE	No	No	No	Yes	Yes	No	No
Industry FE	No	No	No	No	No	Yes	Yes
Observations	27,550	20,787	20,787	20,787	20,787	20,787	20,787
Number of Firms	2,761	2,432	2,432	2,432	2,432	2,432	2,432
Adjusted R^2	0.003	0.353	0.374	0.132	0.157	0.366	0.387

Lastly, I perform robustness tests for my *Cash/Assets* regressions by adding the two variables *LastRating* and *LastInvGrade* to the models. The results can be found in Table XIV. Again, I selected two regressions of each model with the highest explanatory power (highest adjusted R^2) from my *NetDebtIssuance* regressions. Panel A shows the results with the *LastRating* variable added to the models while keeping everything else unchanged. The hypothesis is that firms with lower ratings are perceived as riskier and should have lower cash holdings. However, the coefficients of *LastRating* are not significant in any regression. Thus, my outcome does not support the assumption that cash holdings correlate negatively with lower ratings. However, adding *LastRating* to my models has no impact on the significance of my explanatory variables and only a little impact on the coefficients. *RatingDc* and *YearsUnrated* still negatively impact *Cash/Assets*. The results in Panel B confirm this outcome. The coefficients of *LastInvGrade* are not significant in any regression. However, adding *LastInvGrade* to my models has no impact on the significance of explanatory variables and only a little impact on the coefficients.

Table XIV: *Cash/Assets* Robustness

This table is divided into two panels. Panel A reports the results for the *Cash/Assets* regressions with *LastRating* added to the models. Panel B shows the regression results with *LastInvGrade* added to the models. All columns represent OLS regressions. Results in columns (1), (3), and (5) include Year and Firm FE. Columns (2), (4), and (6) include Year and Industry FE. I use the same control variables as in Table V, but I do not report them for brevity and clarity. Standard errors are clustered at the firm level to adjust for heteroskedasticity and autocorrelation. The p-values are presented in parentheses.

Panel A: *LastRating* added to the models						
	Cash/Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
RatingDc	0.016	0.015				
	(<0.01)	(<0.01)				
YearsUnrated			0.002	0.002		
			(<0.01)	(<0.01)		
YearsRated					-0.000	-0.000
					(0.13)	(0.08)
LastRating	-0.000	0.000	-0.000	0.000	-0.001	0.000
	(0.69)	(0.70)	(0.64)	(0.65)	(0.41)	(0.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	20,482	20,483	20,484	20,484	20,484	20,484
Number of Firms	2,428	2,428	2,428	2,428	2,428	2,428
Adjusted R^2	0.158	0.392	0.158	0.393	0.159	0.391

Table XIV continued

Panel B: *LastInvGrade* added to the models						
	Cash/Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
RatingDc	0.016	0.017				
	(<0.01)	(<0.01)				
YearsUnrated			0.002	0.002		
			(<0.01)	(<0.01)		
YearsRated					-0.000	-0.000
					(0.19)	(0.11)
LastInvGrade	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.23)	(0.23)	(0.21)	(0.21)	(0.22)	(0.23)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes
Observations	20,785	20,786	20,787	20,787	20,787	20,787
Number of Firms	2,432	2,432	2,432	2,432	2,432	2,432
Adjusted R^2	0.376	0.389	0.376	0.389	0.374	0.387

5. Limitations & Further Research

This section shows the limitations of my analysis and proposes areas for future exploration. One limitation is the time span of my analysis. The availability of S&P domestic long-term issuer credit ratings in the Compustat database ends in early 2017. Therefore, my analysis cannot capture the latest trends and developments that might have occurred in more recent years after 2017. Another major limitation of my research is my assumption that credit ratings from other CRAs, like Moody's and Fitch Ratings, are perceived as perfect substitutes by investors. According to White (2013), the rating market is dominated by S&P and Moody's with approximately 40% market share each, while Fitch shows a market share of 15%. Therefore, another possible explanation of my findings is that firms with rating discontinuity actually obtained a rating from a different CRA which investors believe to be less valuable. Since I do not have rating information from other rating agencies available, I cannot control for issuer shopping, thus I cannot disprove this alternative hypothesis explaining the differences in capital structure. Another concern is the fact that the group of interest, meaning firms with rating discontinuity, only accounts for 9% of total observations and therefore may not be adequately represented in the sample. This could potentially impact the generalizability of the findings and limit the accuracy of conclusions drawn specifically for that group. As in every regression analysis, unobserved or unaccounted variables can influence the relationship between the dependent and independent variables, leading to an omitted variable bias.

To address some of these issues, I first suggest extending my work by adding rating information from other CRAs to the analysis. By doing this, one can control for issuer shopping and thus making stronger statements about the actual effect of rating discontinuity and the shopping effect on capital structure. As an extension of my research, I propose examining whether 'Investment Grade' and 'Speculative Grade' rated firms are more or less affected by rating discontinuity. Further, it would be interesting to see whether my results hold in other markets than the United States or whether other dimensions like firms' investments or sales growth are similarly affected.

6. Conclusion

This dissertation compares rated and formerly rated firms regarding their capital structure. I use debt-to-equity issuance, leverage, net debt issuance, and cash holdings of firms as proxies for their capital structure decisions. The coefficients for rating discontinuity are significant at the 1% significance level in all models. The results suggest that we do observe rating discontinuity within this sample and that firms experiencing periods without S&P rating and continuously rated firms present differences in capital structure. Depending on the model, firms with rating discontinuity show 1.2 to 1.9 percentage points lower debt-to-equity issuance, 8.1 to 13.3 percentage points lower book leverage, 7.2 to 11.6 percentage points lower market leverage, 1.6 to 2.2 percentage points smaller net debt issuance and 0.9 to 4.4 percentage points higher cash holdings. All these effects are large and do not occur immediately after rating discontinuity but strengthen over time. However, as pointed out in my limitations section, this work cannot prove the existence of rating discontinuity. Without assuming that ratings from other CRAs are perfect substitutes for S&P ratings, there is still the possibility of other aspects, like issuer shopping, causing those differences in capital structure.

Regarding the reputation effect through the stability of rating information, the findings suggest a small impact on net debt issuance and leverage levels. When adding rating information to the models, results show a 0.1 percentage points increase in book leverage and net debt issuance and a 0.2 percentage points increase in market leverage with every year being rated. All in all, this research contributes to the existing literature by providing valuable insights into the factors influencing firms' financing decisions, with important implications for companies, policymakers, and investors who seek to make informed choices regarding firms' capital structure.

References

Almeida, H., Cunha, I., Ferreira, M. A., & Restrepo, F. (2017). The Real Effects of Credit Ratings: The Sovereign Ceiling Channel. *The Journal of Finance*, *72* (1).

Alp, A. (2013). Structural Shifts in Credit Rating Standards. *The Journal of Finance*, *68* (6).

Baghai, R. P., Servaes, H., & Tamayo, A. (2014). Have rating agencies become more conservative? Implications for capital structure and debt pricing. *Journal of Finance*, *69* (5).

Berger, P. G., Ofek, E., & Yermack, D. L. (1997). Managerial Entrenchment and Capital Structure Decisions. *The Journal of Finance*, *52* (4).

Bolton, P., Freixas, X., & Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, *67* (1).

Boot, A. W. A., Milbourn, T. T., & Schmeits, A. (2006). Credit Ratings as Coordination Mechanisms. *Review of Financial Studies*, *19* (1).

Credit Rating Agency Reform Act. (2006). *15 USC 78o–7 note,* United States of America.

Donaldson, G. (1961). *CORPORATE DEBT CAPACITY. A Study of Corporate Debt Policy and the Determination of Corporate Debt Capacity*.

Executive Office of the President of the United States, & Office of Management and Budget. (2022). *NORTH AMERICAN INDUSTRY CLASSIFICATION SYSTEM (NAICS)*.

Faulkender, M., & Petersen, M. A. (2006). Does the source of capital affect capital structure? In *Review of Financial Studies* (Vol. 19, Issue 1, pp. 45–79). Oxford University Press.

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate Finance: evidence from the Field. In *Journal of Financial Economics* (Vol. 60).

Huang, Y. L., & Shen, C. H. (2015). Cross-country variations in capital structure adjustment-The role of credit ratings. *International Review of Economics and Finance*, *39*.

Jorion, P., Shi, C., & Zhang, S. (2009). Tightening credit standards: The role of accounting quality. *Review of Accounting Studies*, *14* (1).

Kisgen, D. J. (2006). Credit Ratings and Capital Structure. *Journal of Finance*, *61* (3).

Kisgen, D. J. (2019). “The Impact of Credit Ratings on Corporate Behavior: Evidence from Moody’s Adjustments.” *Journal of Corporate Finance*, *58*.

Kraus, A., & Litzenberger, R. H. (1973). A STATE-PREFERENCE MODEL OF OPTIMAL FINANCIAL LEVERAGE. *The Journal of Finance*, *28* (4).

Millon, M. H., & Thakor, A. V. (1985). Moral Hazard and Information Sharing: A Model of Financial Information Gathering Agencies. *The Journal of Finance*, *40* (5).

Modigliani, F., & Miller, M. H. (1963). Corporate Income Taxes and the Cost of Capital: A Correction. *The American Economic Review*, *53* (3).

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87* (3).

Titman, S., & Wessels, R. (1988). The Determinants of Capital Structure Choice. *The Journal of Finance*, *43* (1).

White, L. J. (2013). Credit Rating Agencies: An Overview. *Annual Review of Financial Economics, 5.*

Wojewodzki, M., Poon, W. P. H., & Shen, J. (2018). The role of credit ratings on capital structure and its speed of adjustment: an international study. *European Journal of Finance*, *24* (9).