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FIRM CREDIT RATING CHANGES, CAPITAL STRUCTURE, AND THE ASYMMETRIC MODERATING ROLE OF DEBT CAPACITY AND FINANCIAL CONSTRAINTS

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Abstract. This study analyzes how debt capacity and financial constraints impact credit rating changes. Using a comprehensive sample of European companies, we analyze rating upgrades and downgrades separately to allow us to uncover whether the effects differ. Our results show that only one of the four commonly used proxies for debt capacity can explain credit rating changes. Specifically, we find that debt capacity can influence both rating upgrades and downgrades, but financial constraints or profitability can only impact rating downgrades. Our results are robust to various model specifications. The Monte Carlo simulation results reveal that uncertainty related to factors causing rating upgrades increases sharply when debt exceeds 30% of total assets. Similarly, when debt exceeds 50% of total assets, uncertainty related to rating downgrades surges.

Keywords: credit rating changes, debt capacity, financial constraints, capital structure, profitability, debt-to-total assets.

JEL Classification: G32, C53.

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1. Introduction

A firm's credit rating significantly influences managerial capital structure decisions. The benefits and costs of credit ratings may explain variations in capital structure beyond traditional theories (e.g., Kisgen, 2006). This study examines how debt capacity and financial constraints drive credit rating changes, assuming these factors act asymmetrically, leading to both upgrades and downgrades.

Debt capacity, rooted in pecking order theory, frames managers' capital structure decisions as constrained by borrowing limits. Literature also highlights financial constraints as a key limitation on such decisions.

Analysis is challenging because rating changes are observable, whereas debt capacity and financial constraints are latent yet materially shape capital structure decisions. This creates a scientific gap. A complete account must incorporate rating dynamics, whose effects are asymmetric: firms expend greater effort to avoid downgrades – especially to speculative grade – often by deleveraging (Begley, 2013). Evidence also indicates that upgrades and downgrades are driven by different factors (Distinguin et al., 2013; Begley, 2013; Lemmon & Zender, 2010).

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While debt capacity suggests a maximum debt level under given conditions, its measurement is less straightforward. Debt is typically scaled by balance sheet items – such as assets, equity, interest expense, EBITDA, or asset tangibility – serving as proxies. However, existing research lacks consensus on its definition, and no study compares which proxy best captures the concept (e.g., Hahn & Lee, 2005; Hess & Immenköter, 2014).

his study offers several contributions. Unlike prior research, we link credit rating changes to debt capacity and financial constraints, addressing their relationship as potentially asymmetric in effect. This asymmetry matters because it may influence findings in studies using these factors as explanatory variables. To our knowledge, we are the first to identify debt capacity measures significantly associated with rating changes. Our results show that debt capacity and financial constraints are important drivers of credit rating changes, though patterns differ for upgrades and downgrades. Findings remain robust across model specifications and controls.

Based on the identified research gap, our study addresses the following research questions:

- **RQ1:** Which debt capacity proxies significantly explain credit rating changes?
- **RQ2:** Do the effects of debt capacity and financial constraints on credit rating changes differ between rating upgrades and downgrades?

The remainder of this paper is structured as follows. Section 2 discusses the extant literature on capital structure theories, debt capacity, financial constraints, and their impact on credit rating changes. Section 3 presents the sample, the concept of the solution, and the control variables. Sections 4 and 5 presents and analyzes the results, respectively. The last section concludes the study.

2. Literature review

2.1. Debt capacity definition

According to Myers (1977), debt capacity represents the point at which an increase in debt reduces a firm's total market value. For Turnbull (1979), debt capacity is the maximum debt that lenders are willing to extend to a firm. Kim (1978) links debt capacity with the maximum amount of debt a firm can incur and repay, as assessed by creditors. Brennan and Schwartz (1978) relate debt capacity to the moment when further debt issues harm the survival probability of a business. Meanwhile, Hahn and Lee (2005) approximate business debt capacity using Almeida and Campallo's (2007) asset tangibility measure. According to Almeida and Campallo (2007), holding pledgeable assets supports more borrowing and thus increases borrowing ability. Rizzi (1994) provides a novel framework for measuring debt capacity from a creditor's viewpoint since practical attitudes on how to define or measure debt capacity are limited. He emphasizes the importance of understanding a firm's expected cash sources and needs within its economic environment. Li et al. (2023) show that high investor sentiment increases leverage, indicating that optimistic market conditions expand debt capacity and promote aggressive capital strategies.

2.2. Debt capacity and capital structure theory

Two competing theories dominate the academic debate on the relationship between debt capacity and a firm's capital structure: trade-off theory (Modigliani & Miller, 1958, 1963; Jensen & Meckling, 1978; DeAngelo & Masulis, 1980) and pecking order hypothesis (Myers, 1984; Myers & Majluf, 1984). While trade-off theory seeks an optimal capital structure, which requires a trade-off between the tax benefits of loans and the costs of financial distress resulting from excessive lending, pecking order theory does not strictly define an optimal capital structure, as changes in debt ratios are driven by the need for external financing and not by any attempts to reach an optimal capital structure (Shyam-Sunder & Myers, 1999). Kisgen (2006) reveals that the effects of ratings on capital structure are complementary to existing capital structure theories, as some situations are not explained by existing capital structure theories.

Shyam-Sunder and Myers (1999) find that the pecking order is "an excellent first-order descriptor" of financing choices in mature corporations. However, Chirinko and Singha (2000) question Shyam-Sunder and Myers' (1999) test and conclude that the tests are unable to assess "plausible patterns" of external funding. Additionally, they document that alternative statistical procedures are required to identify the determinants of capital structure and "discriminate among competing hypotheses." Lemmon and Zender (2010) modify Shyam-Sunder and Myers' (1999) test by reflecting heterogeneity in the level of debt capacity across firms and show that firms with unconstrained debt capacity prefer debt, while those firms with limited debt capacity prefer equity financing.

Bolton and Freixas (2000) propose a simple model of the capital market and corporate finance closely based on pecking order theory, in which firms endogenously make decisions on their financial structure. As Lemmon and Zender (2010) note, the model is "empirically implementable" to define debt capacity. The model derives the capital market equilibrium in which firm funding is segmented into three categories. The riskiest firms have minimal or no access to external capital or are constrained to issue equity. Less risky firms normally obtain bank loans for financing. Firms with the lowest risk use securities markets and benefit from avoiding intermediation costs; thus, they have the highest debt capacity.

Leary and Roberts (2010) explore the applicability of the pecking order theory, assuming firms can borrow up to the average leverage ratio of investment-grade peers. Pascual and Palmeiro (2009), analyzing European firms, argue that no single capital structure theory universally explains financial behavior, though the pecking order holds more validity for firms facing high information asymmetry and sufficient debt capacity. Hess and Immenköter (2014) note that managers avoid surpassing critical debt thresholds, aligning with the pecking order view that adverse selection costs shape debt capacity and encourage equity financing.

Lemmon and Zender (2010) present a model integrating pecking order and trade-off theories under asymmetric information, extending the analyses of Myers and Majluf (1984) and Myers (1984). They identify liquidation value as a proxy for debt capacity, marking the limit beyond which adverse selection prevents further borrowing, and note that optimal debt levels may fall below this threshold. More recently, Czerwonka and Jaworski (2021) find that pecking order theory effectively explains SME capital structures in Central and Eastern Europe, as these firms maintain debt capacity. Gan et al. (2022), using a dynamic trade-off model, show that firms combining bank and market debt invest more rapidly and face less debt overhang than those relying solely on market debt.

2.3. Estimating debt capacity using credit ratings

De Jong et al. (2011) follow Shyam-Sunder and Myers' (1999) interpretation of pecking order theory and use a firm's credit rating to derive an estimate of the marginal debt ratio that would make a firm lose investment grade rating, that is, a debt ratio that increases the probability of obtaining a speculative grade to 0.5. Similarly, Hess and Immenkötter (2014) estimate debt capacity as critical debt that, when exceeded, leads to a downgrade in credit rating by a notch, but not necessarily to speculative grade.

Recently, credit ratings have been criticized because they react slowly to deteriorating financial conditions (e.g., Blöchlinger & Leippold, 2018; Aggarwal et al., 2023). Aggarwal et al. (2023) show that unlike models based on market information such as Merton's (1974) distance to default models, credit ratings do not immediately reflect the worsening financial health of a firm. In contrast, Gredil et al. (2023) show that rating changes are correlated with future defaults of up to the next 4 years, even after controlling for market-based measures of credit risk as proposed by Campbell et al. (2008) and Duan et al. (2012).

Despite criticism, credit ratings remain a useful proxy for debt capacity. Firms actively avoid downgrades, especially by reducing leverage when ratings are at risk (Begley, 2013). Distinguin et al. (2013) show that factors influencing upgrades differ from those affecting downgrades in Asian banks. Regulators also incorporate ratings into microprudential risk assessments (Jeon & Lovo, 2013). Gredil et al. (2023) find that rating downgrades respond more to cash-flow news than to discount rate changes, which may reflect market noise from behavioral or frictional factors.

Changes in cash flows are among the factors that link credit rating downgrades to lowering debt capacity. Lian and Ma (2021) state that lenders often limit the maximum level of debt provided to a business (cannot exceed a multiple of EBITDA over the past 12 months) by legally binding earning-based constraints. Lian and Ma (2021) further point out that approximately 60% of large US non-financial companies have earnings-based covenants explicitly written into their debt contracts. Abid and Abid (2023) explore how credit ratings influence firms' decisions about their optimal capital structures by applying a novel methodological framework. They show that the estimated average optimal debt ratios are relatively high and exhibit distinct patterns both across and within investment- and speculative-grade firms.

2.4. Rating upgrades and downgrades and their relationship to debt capacity

Mokoaleli-Mokoteli (2019) investigate how changes in firms' credit ratings affect the stock prices of companies listed on the Johannesburg Stock Exchange between 2005 and 2015. They conclude that rating upgrades are generally anticipated by the market and thus do not significantly impact equity prices, while rating downgrades contain new price-sensitive information and thus can negatively affect future earnings and cash flows and lead to divestments. Kim and Sohn (2008) use a random-effects multinomial regression model to estimate rating upgrade/downgrade probabilities on a sample of rating transition data of Korean firms from 2000 to 2004. They reveal that retained earnings versus total assets is the most influential factor in predicting the transition to rating upgrades.

Based on a large sample of US financial data over the period 1990–2011, Kim et al. (2013) examine firm managers' incentives to influence firms' earnings to manage rating downgrades or upgrades. Although they find a positive relationship between real activity earnings management (RM) and rating upgrades, they do not observe a relationship between RM and rating downgrades because of the need for effective earnings management. Goebel and Kemper (2022) examine the relationship between rating levels and subsequent annual net debt changes. They find that firms experiencing notch-level rating adjustments do not exhibit significantly lower net debt levels, more substantial net debt reductions, or a higher likelihood of upgrades than firms undergoing non-notch rating changes.

Hung et al. (2017) find that firms exploit information asymmetry by increasing debt financing – mainly through new issuances – prior to credit rating downgrades, but make no significant adjustments before upgrades. Samaniego-Medina and di Pietro (2019), studying European listed firms, show that rating modifiers slow convergence toward target leverage, especially when ratings threaten investment-grade status, such as BBB.

2.5. Financial constraints as an obstacle in external financing and capital structure adjusting

Fazzari et al. (1988) show that the investment decisions of financially constrained firms are more sensitive to the availability of internal cash flows than they are in the case of unconstrained firms. Beck et al. (2006) consider a business as being financially constrained, *"if a windfall increase in the supply of internal funds results in a higher level of investment spending."* Financially constrained businesses are more dependent on external funds, making them more sensitive to fluctuations in credit markets (Jin et al., 2018; Janoskova et al., 2024; Aleknevičienė & Stralkutė, 2023), limiting their growth potential and ability to invest (Erdogan, 2018), and affecting their default probability (Musso & Schiavo, 2008; Karas & Režňáková, 2021, 2023).

While financial constraints are more common among SMEs (Belas et al., 2024; Civelek et al., 2023; Kuděj et al., 2023; Śliwiński, 2024), firms with low credit ratings may also face limitations compared to investment-grade businesses. Many firms aim for a target capital structure (Kayhan & Titman, 2007), but constrained firms struggle to adjust due to reliance on external financing (Valaskova et al., 2023), making them more vulnerable to credit market fluctuations (Jin et al., 2018). Larger, older, and foreign-owned firms typically face fewer financing barriers. Financial constraints influence capital structure decisions (Meluzín et al., 2021; Beck et al., 2006), and unconstrained firms with strong cash flows may repay debt, repurchase shares, or pay dividends (Faulkender et al., 2012). In contrast, constrained firms have limited access to external capital (Beck et al., 2006; Ullah, 2020; North et al., 2010) and tend to offer lower dividend payouts (Cleary, 2006; Musso & Schiavo, 2008).

Financially constrained businesses are highly sensitive to the availability of internally generated funds (Fazzari et al., 1988). In addition, financially constrained firms facing the risk of downgrading are more cautious when conducting acquisitions (Kang, 2022). The relationship between downgrade risk and acquisition propensity is likely affected by concerns that the risks associated with acquisitions may cause rating deterioration. Similarly, companies affected by higher credit financial constraints are more sensitive to cash holdings, investments, and financing their needs by loans (Chien et al., 2023). Therefore, the risk of downgrading has a significant impact on cash flow allocation and affects financial constraints on cash flow sensitivity because of precautionary motivations or limited access to external funds.

3. Methodology and research sample

This study evaluates the explanatory power of alternative debt capacity indicators (proxies) within the framework of a linear probability model. For the significant indicators, we control for the influence of other relevant factors using alternative specifications of the logit and ordinal logit models. The explanatory variables used are the corresponding indicators of changes in credit ratings.

3.1. Research sample

We utilize a sample of 1,801 companies with Moody's long-term firm ratings from EU27 countries, Norway, Switzerland, and the United Kingdom. Data are collected from 2011 to 2020, and the final sample includes 9,561 company-year observations. Because companies do not regularly report ratings, we only use observations with non-missing ratings. In this case, the control variables, expressed as changes or growth rates, are expressed relative to the year with the latest known rating. The lagged variables correspond to the values in the year of the previous known rating. We also use a sample of firms in which the last available ratings replace the missing ratings for robustness checks. However, this approach does not change the main conclusions.

In our final sample, we omit all observations with negative values of the debt-over-equity variable. We also restrict the sample to firms outside the finance and banking industries (NACE Category K). The data for individual company ratings is based on Moody's long-term ratings classification scale (which includes 21 grades ranging from "Aaa" to "C"). As part of a robustness check, we also utilize the classification based on short-term ratings using the VMIG scale: "VMIG 1," "VMIG 2," "VMIG 3," and "SG". "VMIG 1" corresponds to short-term ratings between "Aaa" and "Aa2," "VMIG 2" includes ratings "Aa3" and "Baa1," "VMIG 3" relates to the long-term ratings "Baa2" and "Baa3," and the speculative grade "SG" encompasses long-term ratings from "Ba1" to "C." Due to the lower variability of changes in the aggregate ratings constructed in this manner, the estimates of the identified effects of the control variables show slightly higher variability. However, the results remain almost the same for the signs of the estimated coefficients. As companies do not regularly report ratings, we use only observations with non-missing ratings. The descriptive statistics of the sample are presented in Appendix Tables A1 and A2, and the variables are listed in Table A3.

3.2. Methodological concept of solution

To analyze credit rating changes, we employ a linear probability model, a binomial logit model, and an ordinal logit model. The dependent variable is constructed based on changes in the published ratings of individual firms. Three situations can occur: a rating upgrade (U), rating affirmation (A), and rating downgrade (D). In our case, we do not distinguish between the extent to which the rating has declined or increased.

First, using a simple linear probability model, we conduct a univariate analysis to investigate the effects of alternative debt capacity proxies on rating changes. We focus on companies with upgraded (dependent variable equals 1) and downgraded (dependent variable equals 0) ratings. The linear probability model (Model 1) takes the following form:

$$dR_{it} = \beta_0 + \beta_1 \cdot DC_{i,t-1} \tag{1}$$

or rather

$$dR_{it} = \beta_0 + \beta_1 \cdot \Delta DC_{i,t}, \tag{2}$$

where dR_{it} equals 1 for observations with upgraded ratings and 0 for companies with downgraded ratings. Companies with affirmed ratings are omitted. As a dependent variable, we consider the alternative debt capacity indicators, DC, in the form of lagged variables, $DC_{i,t-1}$, and their changes, $\Delta DC_{i,t}$. The time index t, indicates the period of the last known rating. The same holds for the difference operator, Δ.

Model 1 aims to select the debt capacity measure that is best linked with rating changes. Once identified, these debt capacity indicators are analyzed using logit and ordered logit models (Models 2 and 3) below. Model 2, which aims to verify the robustness of the results by controlling for other factors that influence credit rating dynamics, is derived using various specifications. We examine the level of lagged debt capacity (defined as debt capacity in the period immediately preceding the last known rating) and the impact of changes in debt capacity.

We use logit models to analyze the effects of the most significant debt capacity measure (resulting from the estimation of Model 1) on rating changes, while controlling for other relevant factors and interaction terms. Our sample consists of three types of companies depending on credit rating changes: upgraded, downgraded, or affirmed. Based on this, we construct logit models for three groups of firms: upgraded (response variable equal to one) and downgraded ratings, upgraded (response variable equal to one) and affirmed ratings, and downgraded (response variable equal to one) and affirmed ratings. The model is as follows:

$$LOGIT_{it} = \beta_0 + \beta_1 \cdot DC_{i,t-1} + \sum_{i=2}^{k} \beta_i \cdot CV_{i,t-1} \quad (3)$$

or rather

$$LOGIT_{it} = \beta_0 + \beta_1 \cdot \Delta DC_{i,t} + \sum_{i=2}^{k} \beta_i \cdot \Delta CV_{i,t}, \quad (4)$$

where $CV_{i,t-1}$ and ΔCV_{it} represent the sets of lagged and differenced control variables, respectively. Thus, we explore whether the rating change is affected by the level of explanatory variables in the past or by their change from the previous period (period with the last known rating). We have incorporated lagged explanatory variables into our models to mitigate the problem of endogeneity and reduce simultaneity bias. While we recognize that using differences may still leave room for some endogeneity, we address this by presenting results from alternative model specifications to demonstrate the robustness of our findings regarding the role of debt capacity indicators. Some explanatory variables are not transformed into lagged variables or differences. To address the industry effect and the effect of last rating assigned, the model is enhanced using corresponding dummy variables and their interactions with debt capacity indicators. The ordinary logit model (Model 3) is as follows:

$$\begin{aligned} LOGIT_{it} &= \beta_0 + \beta_1 \cdot DC_{i,t-1} + \sum_{i=2}^{k} \beta_i \cdot CV_{i,t-1} + \sum_{i=1}^{l} \gamma_{1i} \cdot IND_{it} + \\ &\delta_{11} \cdot R_{good,it} + \delta_{12} \cdot R_{nearSG,it} + \sum_{i=1}^{l} \gamma_{2i} \cdot IND_{it} \cdot DC_{i,t-1} + \delta \\ &{}_{21} \cdot R_{good,it} \cdot DC_{i,t-1} + \delta_{22} \cdot R_{nearSG,it} \cdot DC_{i,t-1} \end{aligned} \quad (5)$$

or rather

$$\begin{aligned} LOGIT_{it} &= \beta_0 + \beta_1 \cdot \Delta DC_{i,t} + \sum_{i=2}^{k} \beta_i \cdot \Delta CV_{i,t} + \sum_{i=1}^{l} \gamma_{1i} \cdot IND_{it} + \\ &\delta_{11} \cdot R_{good,it} + \delta_{12} \cdot R_{nearSG,it} + \sum_{i=1}^{l} \gamma_{2i} \cdot IND_{it} \cdot \Delta DC_{i,t} + \\ &\delta_{21} \cdot R_{good,it} \cdot \Delta DC_{i,t} + \delta_{22} \cdot R_{nearSG,it} \cdot \Delta DC_{i,t}, \end{aligned} \quad (6)$$

where $R_{good,it}$ is a dummy variable that takes the value of 1 when the last assigned rating is of the VMIG 1 category (good rating), and 0 otherwise; $R_{nearSG,it}$ is a dummy variable that takes the value of 1 when the last assigned rating is of the VMIG 2 or VMIGG 3 category, and 0 otherwise (near speculative grade). The variable *IND* originally consisted of multiple industry categories. We have converted this variable into a set of dummy variables according NACE main sections classification. In our final models, we have worked with five dummy variables in the regression model, corresponding to the NACE categories C (Manufacturing, dummy variable IND_{1t}), G (Wholesale and retail trade, repair of motor vehicles and motorcycles, IND_{2t}), I (Accommodation and food service activities, IND_{3t}), J (Information and communication, IND_{4t}), and M (Professional, scientific and technical activities, IND_{4t}).

In Model 3, we use all categories of firms as our response variables by considering the possible homogeneous effect of explanatory variables on rating category changes. Thus, the dependent variable is an ordinary variable representing downgraded, affirmed, and upgraded ratings. Table 1 presents the coding of all dependent variables.

Table 1. Dependent variable coding per model specification (source: author's work)

Model 2 subvariant	Dependent variable value per rating change			
	Upgrade	Affirmation	Downgrade	Observations
U (1) vs D (0)	1		0	506
U (1) vs A (0)	1	0		1136
D (1) vs A (0)		0	1	1142
Ordinal	3	2	1	1755

Comparing the coefficients and significance of Model 2 subversions allows us to identify potential asymmetrical effects of the debt capacity, financial constraints measure, and control variables.

3.3. Potential debt capacity proxies

The concept of debt capacity gravitates around the maximum value of debt. However, for modeling purposes, the value of debt must be scaled through other accounting measures, resulting in various proxies of debt capacity. The added variable not only scales the value of debt but also represents a factor that constrains borrowing. Generally, maximum debt is limited either by asset value or by cash flow value. Lian and Ma (2021) find that 20% of corporate debt of non-financial US companies is tied to specific physical assets, which can be evaluated or repossessed on a standalone basis (referred to asset-based lending), whereas 80% of corporate debt is based on the value of cash flow from firm's continuing operations (referred as cash flow-based lending). They reveal that lenders often focus on current EBITDA as the principal metric of cash flow value.

Proxies for debt capacity in the form of debt over total assets (DTA) or asset tangibility (Almeida & Campallo, 2007) reflect the asset-based lending approach. This approach is adopted by de Jong et al. (2011), Lu et al. (2024), and Lee et al. (2021). Meanwhile, proxies for debt capacity in the form of debt over EBITDA (DEBITDA) or EBIT over interest expense (EBITInt) reflect cash flow-based lending. Since many corporate assets are specialized and illiquid (e.g. Altig et al., 2011), many companies favor cash-flow-based lending. In effect, cash flow-based lending is popular for large companies and rare for small companies (Lian & Ma, 2021).

These proxies were selected because they represent two dominant theoretical perspectives on debt capacity: the asset-based lending approach (DTA, asset tangibility) and the cash-flow-based lending approach (debt-to-EBITDA, interest coverage), both widely discussed in prior literature (e.g., Almeida & Campallo, 2007; Lian & Ma, 2021).

We compare four debt capacity proxies: debt over equity (DE), DTA, EBITInt, and DEBITDA. These ratios are expected to have a significant impact on rating changes. Table 2 presents the effects of the indicators.

Table 2. Impact of changes of debt capacity indicators on credit rating downgrades (source: authors' findings based on Kemper's (2020) analysis)

Variable	Direction of variable change	Impact on credit rating	Reasoning for the rating change
Debt over equity (D/E)	Increase ↑	Downgrade (↓)	Firms with rising debt ratios may signal that they are unable to cover their expenses with their operating cash flows. They need additional external funds to sustain their business.
Debt over total assets (D/TA)	Increase ↑	Downgrade (↓)	
Interest cover (EBIT/Interest expense)	Decrease ↓	Downgrade (↓)	Firms with a decreasing ratio may signal that they are increasingly burdened by debt service. In the long run, this could negatively affect their ability to meet interest expenses.
Profitability (EBITDA/Assets)	Decrease ↓	Downgrade (↓)	Lower profitability ratios may indicate weaknesses in sales when the firm is unable to charge appropriate prices for its products or costs when the firm management failed to maintain them at a stable level.

3.4. Approximating the level of financial constraints and its relationship to capital structure and credit ratings

Financial constraints are expected to increase default risk (Musso & Schiavo, 2008), leading to lower credit ratings. In addition, financial constraints are closely related to the financial structure of a business, as businesses that carry high debt are considered high-risk and have difficulty obtaining additional external funds (e.g., Berman & Héricourt, 2010; Fauceglia, 2015; Musso & Schiavo, 2008). Since financial constraints are directly unobservable, the literature often relies on different firm-specific proxies such as size, age, or liquidity when creating a model for them. Younger, smaller, and less-liquid firms are considered more constrained (see Beck et al., 2006; Fauceglia, 2015; D'Souza et al., 2017; Ullah, 2020).

Thus, we address the financial constraint factors through Hadlock and Pierce's (2010) size-age index (SAI). The advantage of using SAI is that it is less correlated with leverage compared to other measures (Lu et al., 2024), allowing us to avoid multicollinearity problem with the firm-specific control variables. The SAI is given as follows:

$$SAI = -0.737 \times \ln(TA) + 0.043 \times (\ln(TA))^2 - 0.040 \times Age, \tag{7}$$

where TA is the book value of total assets and Age is the number of years starting from the date of firm establishment to the year of the last financial report.

Using SAI, Lu et al. (2024) defines age as the number of years a firm has been in the Compustat database with a non-missing stock price. A larger SAI value is related to smaller, younger, and more financially constrained firms. According to Kim et al. (2023), firms with investment grades encounter few financial constraints; thus, the SAI values for them are lower.

3.5. Control variables

The proxies for debt capacity (especially debt-equity ratio or interest cover) represent variables with high dispersion, often reaching outlier values, even with businesses that share the same (investing grade) rating notch. To analyze the relationship between debt capacity proxies and given rating notches, we control for factors that might explain the differences in debt levels adopted by given businesses. Lemmon et al. (2008) show that capital structure is mainly driven by an unobserved time-invariant effect and is largely unexplained by previously identified determinants (e.g., size, profitability, market-to-book, and industry). This has led to the adoption of a greater variance of control variables. In this study, we employ the following control variables:

I. **R&D expenditures (RDTA):** We use R&D expenditures scaled by the value of total assets. Studies on corporate leverage often adopt controls for R&D expenditures (e.g., Faulkender et al., 2012; Lu et al., 2024). When analyzing leverage factors, R&D expenditures must be controlled as a positive interdependent relationship is observed between the debt ratio and R&D intensity (Fryges et al., 2012). This suggests that a higher share of debt in the capital structure allows for more R&D in young firms, while a higher intensity of R&D expenditures allows for a higher loan share. R&D intensity is negatively associated with credit ratings due to the general uncertainty surrounding R&D projects (Brasch et al., 2022). Furthermore, firms reduce their R&D expenditures when they are trying to improve their credit ratings (Begley, 2015).

II. **Asset tangibility:** Holding pledgeable assets supports more borrowing (Almeida & Campallo, 2007) and affects cash holdings and investments (Boasiako et al., 2022). Moreover, asset pledgeability is represented by a firm's tangibility measure specified as tangible assets over total assets (FATA) (e.g., Lee et al., 2021). Lastly, a positive relationship is observed between tangibility and credit ratings (Dang et al., 2022; Hung et al., 2022).

III. **Profitability:** Most studies on corporate financial decisions adopt profitability as a control variable (e.g., Tang, 2009; Lee et al., 2021; Lu et al., 2024). Tang (2009) reveals that profitability can be used either as a proxy for the internal cash flow available for investment funding or as a proxy for the shielding of taxable income (Myers, 1984; Leary, 2009). To control for profitability, we use the EBIT over the total assets variable (EBITTA). As Dang et al. (2022) and Hung et al. (2022) show, a positive relationship between profitability and credit ratings is expected.

IV. **Level of financial market development:** The firm's ability to adjust leverage also depends on its incentive to enter capital markets for reasons other than transaction costs (Faulkender et al., 2012). To control for cross-country differences in financial market development and economic development, we follow Beck et al. (2006) and use the GDP per capita measure at current prices in EUR (GDPpc). firms reduce their share repurchases and total payouts during a crisis, and this reduction is more significant for highly leveraged firms with low cash holdings (Bliss et al., 2015). This reduction is more significant for firms in which marginal borrowing comes from cash flow-based debt (Kariya, 2022). Controlling cross-country differences in economic development may shed more light on debt levels and their variability. Moreover, we address this term in interaction with financial constraints factors, since macroeconomic conditions are more significant for unconstrained firms than for constrained firms (Korajczyk & Levy, 2003). GDP per capita has a negative relationship with firms' credit ratings (Borensztein et al., 2013; Hung et al., 2022), as there are more firms with ratings below the sovereign rating in high-income countries (Borensztein et al., 2013).

V. **Industry (IND):** Control for industry-specific factors is necessary due to several reasons. First, a firm's ability to issue asset-based borrowing varies between industries, owing to specific assets and redeployability (Kariya, 2022). Second, asset lending might not only be typical for small companies but also for companies in other industries such as airlines and utilities (Lian & Ma, 2021).

VI. **Cash holdings:** The more cash a firm holds, the higher its ability to repay the debt and the greater its debt capacity (Francis et al., 2014). An increase in cash holdings lead to higher leverage deviations, signifying enhanced debt capacity (Lu et al., 2024). Cash holdings are measured as cash and cash equivalents over total assets (CTA). Moreover, an increase in ratings leads to an increase in cash holdings, and this effect is more pronounced when firms become sensitive to rating changes (i.e., when their credit ratings have just moved to the plus or minus levels) and increase their cash holdings (Joe & Oh, 2018).

VII. **Debt maturity and rollover cost:** Businesses with high ratings are less concerned about debt capacity and rollover cost; thus, they can shorten their debt maturity without having to reduce their leverage (Pour & Khansalar, 2015; Lemmon & Zender, 2010; Johnson, 2003). We use term structure of interest rate (TSIR) to proxy for market expectations about interest rates and control for cross-country differences (Pour & Khansalar, 2015; Brick & Ravid, 1985). Specifically, we adopt TSIR, which is the difference between long-term interest rates (yield of government bonds maturing in ten years) and short-term interest rates (yield of three-month treasury bills), from the EUROSTAT database. The tax benefit of using long-term debt increases when the term structure of the interest rate slopes upward (Brick & Ravid, 1985). Furthermore, we use the share of long-term debt over total debt (LTDTD) as a proxy for debt maturity at the firm level. A negative relationship between credit rating and debt maturity is expected, as a one-letter deterioration in the S&P bond rating increases the debt maturity structure by 1.44 years (Stohs & Mauer, 1996).

VIII. **Effective tax rate (ETR):** We use ETR for two reasons. First, in line with trade-off theory, leverage has a positive relationship with effective tax rate, as businesses that use more debt take advantage of higher tax savings (Fama & French, 2002). Moreover, tax shields impact capital structure choices (Mackie-Mason, 1990; Graham, 1996). Second, we issue ETR to control for cross-country differences in corporate income taxes. Specifically, we calculate ETR as income tax over EBIT. A negative relationship between tax rate and credit ratings is expected, as a higher tax rate increases firms' cash flow volatility (Heider & Ljungqvist, 2015) that affects firms' ability to meet debt obligations (Douglas et al., 2016).

4. Results

We screen potential debt capacity measures and answer the question of which competing debt capacity proxies best capture changes in rating grades. We estimate Equations (1) and (2) separately for each potential debt capacity proxy. We use a sample of companies in which the dependent variable equals 1 for upgraded rating and 0 for downgraded rating. Table 3 presents the estimation results.

Table 3. Estimated linear probability models (Model 1) (source: authors' calculations based on data from the Orbis database)

Variable	1	2	3	4	5	6	7	8
	DTA	DTA	DE	DE	DEBITDA	DEBITDA	EBITInt	EBITInt
	lagged	change	lagged	change	lagged	change	lagged	change
Coef. Est.	–0.256**	–1.677***	–0.00000	0.00000	0.00001	–0.00002	0.003***	0.00004
Std.dev.	(0.119)	(0.262)	(0.00000)	(0.00000)	(0.00003)	(0.00002)	(0.001)	(0.00004)
Constant	0.664***	0.481***	0.488***	0.487***	0.482***	0.482***	0.462***	0.482***
	(0.086)	(0.022)	(0.023)	(0.023)	(0.025)	(0.025)	(0.024)	(0.024)
Observations	475	475	475	475	414	412	441	437
R^2	0.010	0.080	0.003	0.002	0.0004	0.001	0.016	0.002
Adjusted R^2	0.008	0.078	0.001	–0.0002	–0.002	–0.001	0.014	–0.0001
F Statistics	4.605**	40.884***	1.283	0.908	0.164	0.501	7.126***	0.940

Note: *** , **, and * indicate significance at the 1%, 5%, and 10% levels. The standard errors are shown in parentheses.

The model is primarily used to determine which debt capacity indicators would be subjected to further analysis. Out of eight analysed debt capacity proxies, only three exhibit a statistically significant effect on rating changes at the 5% level of significance. Low R-squared values are typical in models with binary dependent variables, particularly in linear probability models. Moreover, in the context of binary outcomes, R-squared is generally a less informative metric for model adequacy than other diagnostics such as classification accuracy or marginal effects. The low R-squared indicates a limited overall model fit. However, this initial analysis was intended primarily as an exploratory step to assess which debt capacity indicators might warrant inclusion in more robust models. Despite the low R-squared, the estimated relationships provide valuable insights into the direction and strength of the associations. The estimated coefficients have the expected variable signs. DTA (both lagged and differenced) and EBITInt (lagged) are the best-performing debt capacity measures, presenting a strong relationship with the rating indicator.

The results confirm that these indicators alone are insufficient to explain rating changes. Next, we analyze the debt over assets indicator by controlling for other effects to better capture the determinants of rating changes. For this purpose, we estimate the models in the forms defined by Equations (3) to (6), where only lagged and differenced debt over total assets are addressed as debt capacity proxies (interest cover does not exhibit a significant effect on rating changes when controlling for other relevant factors).

4.1. Logit and ordinal logit models with lagged variables

Table 4 presents the results of model estimation using lagged variables. Each variant of the model is derived by adopting various combinations of control variables. We use the variance inflation factor (VIF) to evaluate collinearity among explanatory variables. A threshold of VIF < 10 is used to indicate acceptable levels of multicollinearity. All variables included in the final model met this criterion. We present the results with statistically significant variables (at the 20% level), both with and without controlling industry and ratings category effects.

Table 4. Coefficients estimations of models with lagged variables (Models 2 and 3) (source: authors' calculations based on data from the Orbis database)

	U (1) vs D (0)		U (1) vs A (0)		D (1) vs A (0)		Ordinal logit	
DTA (lagged)	−0.887	−1.062*	−0.968**	0.208	0.340	1.079*	−0.541	−0.637*
	(0.562)	(0.566)	(0.454)	(0.658)	(0.440)	(0.637)	(0.362)	(0.357)
SAI	−0.307***		−0.164**			0.125*	−0.147**	
	(0.103)		(0.081)			(0.076)	(0.060)	
TSIR	0.232***	0.174**	0.078*				0.090**	0.058
	(0.079)	(0.080)	(0.046)				(0.037)	(0.037)
ETR (lagged)							0.003	0.004*
							(0.002)	(0.002)
CTA (lagged)			1.545	1.352				
			(0.940)	(1.001)				
FATA (lagged)								
EBITTA (lagged)	6.807***	7.610***		1.819	−6.945***	−6.182***	4.528***	5.203***
	(1.668)	(1.736)		(1.304)	(1.360)	(1.368)	(0.962)	(0.982)
LTDTD (lagged)	−1.145**						−0.474*	
	(0.514)						(0.288)	
Industry dummy ("I")								−13.211**
								(6.240)
Industry dummy ("J")		−0.815*						
		(0.486)						
R_{good}		−1.698***		0.395		−0.306		−0.921***
		(0.400)		(1.325)		(0.248)		(0.199)
$R_{rnearSG}$		−0.797***		0.315		0.431		−0.540***
		(0.218)		(0.683)		(0.646)		(0.135)
DTA (lagged)*Industry dummy ("I")								18.452**
								(8.485)
DTA (lagged)*R_{good}				−3.774*				
				(2.146)				
DTA (lagged)*$R_{rnearSG}$				−2.376**		−1.371		
				(1.008)		(0.894)		
Intercept	−1.219*	0.458	−1.786***	−0.827	−1.130***	−0.698		
	(0.634)	(0.472)	(0.504)	(0.506)	(0.330)	(0.608)		

End of Table 4

	U (1) vs D (0)		U (1) vs A (0)		D (1) vs A (0)		Ordinal logit	
Observations	455	455	970	972	1,030	1,030	1,207	1,207
Accuracy (cutoff = 0.5)	0.622	0.654	0.777	0.778	0.777	0.778	0.630	0.630
AUC	0.674	0.722	0.584	0.710	0.617	0.633		

Note: ***, **, and * indicate significance at the 1%, 5%, and 10 % levels, respectively. The TSIR and SAI variables are not lagged because they are treated as exogenous effects. The standard errors are shown in parentheses. The meanings of the response variables are presented in Table 1.

As shown in Tables 4 and 5, the debt capacity proxies (lagged and differenced DTA indicators) are statistically significant at the 5% level and remain robust across model specifications. Their signs align with economic expectations: higher past or increasing debt capacity raises the probability of a rating downgrade, revealing asymmetries in the factors driving rating changes.

When comparing rating upgrades and downgrades ("U (1) vs D (0)"), lagged DTA retains strong explanatory power, while the industry effect is significant for NACE category "J," whose firms show a lower probability of upgrades. Considering rating categories, firms with top short-term ratings, R_{good} ("VMIG 1") are more prone to downgrades than those near speculative grade, R_{nearSG} ("VMIG 2" and "VMIG 3"). In our approach, the reference category corresponds to the firms rated as speculative. The financial constraint proxy (SAI) is significant only when industry and rating quality effects are excluded, whereas TSIR consistently shows the expected sign.

In models comparing upgrades or downgrades with affirmations ("U (1) vs A (0)" and "D (1) vs A (0)"), lagged DTA remains significant. TSIR is not significant, while lagged EBITTA proves to be a relevant factor in explaining the probability of a rating downgrade only. Industry and rating effects are generally insignificant in these models.

Using an ordinal logit model confirms the significance of lagged DTA. An industry effect of the NACE category "I" further deepens the impact of debt capacity on rating changes. Additionally, the quality of the last rating effect is significant, manifesting a stronger effect when the last rating was within the best aggregated category of "VMIG 1" compared to the category belonging to the near speculative grade.

We find asymmetric effects between rating upgrades and downgrades. TSIR influences only rating upgrades, while lagged profitability (EBITTA) reduces the probability of downgrades but not upgrades. The last rating effect (both "last good" and "near SG") magnifies the effect of the lagged debt capacity measure, where the negative signs mean that these factors additionally lower the probability of a rating upgrade. In contrast, this effect is more pronounced for the "last good" than for the "near SG" grades. CTA, rather than profitability, plays a more relevant role in explaining upgrades. Aggregating industries into four broader groups reveals no significant interactions between debt capacity and industry effects. Likelihood ratio (LR) tests confirm that all full models fit significantly better than their null counterparts, validating the robustness of the results.

The estimated models demonstrate acceptable performance, as indicated by their prediction accuracy and area under the ROC curve (AUC). While some AUC values exceed 0.6, indicating performance better than random guessing, we acknowledge that this level of discriminatory power remains modest. On the other hand, AUC values above 0.7 suggest fair predictive ability. Although the results appear robust for analytical purposes and in assessing the role of debt capacity indicators, caution is warranted when interpreting them for predictive purposes. The predictive power might be further improved by enhancing the model specification and collecting more observations. The lower accuracy of the ordered logit model suggests that the effects of explanatory variables on rating changes and confirmations are heterogeneous, as supported by the varying results across logit models. Nonetheless, lagged debt capacity and lagged profitability (EBITTA) consistently emerge as the key determinants, regardless of model specification.

4.2. Logit and ordinal logit with variables in differences

To verify the robustness of the results and assess the impact of varying control variables, we analyze changes in debt capacity measures and other controls. Table 5 summarizes the estimated models.

Table 5. Coefficients estimations of models with differenced variables (Models 2 and 3) (source: authors' calculations based on data from the Orbis database)

	U (1) vs D (0)		U (1) vs A (0)		D (1) vs A (0)			Ordinal logit	
DTA (change)	–10.595***	–8.478***	–4.859***	–4.412***	5.239***		5.073***	–5.783***	–10.343***
	(1.902)	(2.153)	(1.181)	(1.210)	(1.140)		(1.225)	(0.866)	(1.518)
SAI			–0.109				0.182**	–0.082	
			(0.082)				(0.082)	(0.058)	
TSIR	0.133*	0.114						0.046	
	(0.079)	(0.082)						(0.037)	
ETR (change)			0.030**	0.032*					
			(0.015)	(0.016)					
CTA (change)	–4.506**	–4.182*	–2.474	–2.115				–2.438**	–2.232**
	(2.009)	(2.182)	(1.603)	(1.624)				(1.046)	(1.064)
FATA (change)					–1.827*		–1.971*		
					(1.051)		(1.082)		
EBITTA (change)	5.319***	5.814***	8.682***	7.880***				2.983***	2.752***
	(2.007)	(2.072)	(1.930)	(1.932)				(1.032)	(1.058)
LTDTD (change)									
Industry dummy ("C")		0.473**		0.303*					0.190
		(0.233)		(0.175)					(0.136)
Industry dummy ("G")							0.001		
							(0.443)		
Industry dummy ("O")									1.330
									(0.995)
Industry dummy ("J")									–0.285
									(0.231)

End of Table 5

	U (1) vs D (0)		U (1) vs A (0)		D (1) vs A (0)			Ordinal logit	
Industry dummy ("M")									–0.182
									(0.211)
R_{good}		–1.570***		–1.743***			–0.534**		–0.793***
		(0.410)		(0.356)			(0.269)		(0.195)
$R_{rnearSG}$		–0.435*		–1.107***			–0.670***		–0.400***
		(0.227)		(0.174)			(0.178)		(0.135)
DTA (change)* Industry dummy ("C")		–7.104*							
		(4.303)							
DTA (change)* Industry dummy ("G")						11.785*			
						(6.996)			
DTA (change)* Industry dummy ("J")								7.359***	
								(2.558)	
DTA (change)* Industry dummy ("M")								6.671***	
								(2.524)	
DTA (change)* R_{good}						–4.765		7.734**	
						(3.669)		(3.080)	
DTA (change) *$R_{rnearSG}$								4.214**	
								(1.818)	
Intercept	–0.383*	0.458	–1.915***	–0.722***	–1.269***	0.120			
	(0.208)	(0.472)	(0.450)	(0.143)	(0.078)		(0.494)		
Obser-vations	437	455	938	938	1,012		1,012	1,173	1,191
Accuracy (cutoff = 0.5)	0.664	0.712	0.777	0.776	0.769		0.776	0.629	0.640
AUC	0.735	0.776	0.676	0.738	0.627		0.635		

Note: ***, **, and *indicate significance at the 1%, 5%, and 10 % levels, respectively. The TSIR and SAI do not differ significantly. The standard deviations are shown in parentheses. The meanings of the response variables are presented in Table 1.

The regressions show that the signs and significance of the differenced debt capacity indicator (DTA) remain consistent with previous results. In the model comparing rating upgrades and downgrades ("U (1) vs D (0)"), the change in DTA exhibits strong explanatory power and expected signs. The industry effect is positive and significant for NACE category "C," indicating a higher probability of upgrades, though its interaction with DTA reverses this effect.

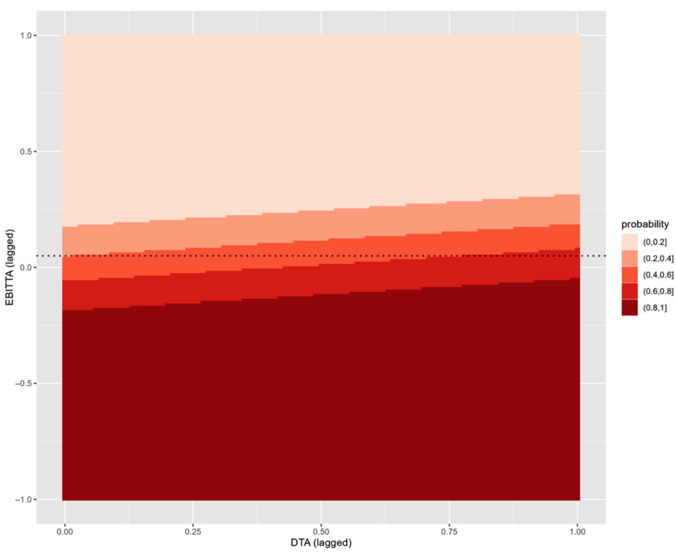
For rating upgrades versus affirmations ("U (1) vs A (0)"), the change in DTA remains significant, while the change in EBITTA is a relevant control factor, unlike the EBITTA level itself. When examining downgrades versus affirmations ("D (1) vs A (0)"), changes in FATA are significant even after accounting for industry and prior rating effects. An interaction term for NACE category "G" shows that higher DTA changes further increase downgrade probabilities.

The ordinal logit model confirms that changes in DTA are robust predictors of rating movements, while changes in CTA and EBITTA also play a role. Industry effects appear mainly in NACE "J" and "M," where positive signs at interaction terms indicate a weaker DTA impact. Firms with higher prior ratings ("good" or "near speculative") are less sensitive to debt capacity changes.

Finally, asymmetric effects emerge: the change in DTA significantly affects both rating upgrades and downgrades, while financial constraints and FATA changes influence only rating downgrades. In contrast, EBITTA changes matter only for rating upgrades. Prior rating quality consistently reduces the probability of an upgrade.

4.3. Monte Carlo simulation results

We simulate the effects of debt capacity (proxied by DTA) on the probability of rating changes using our estimated models. DTA ranges from 0 to 1 (excluding negative equity), and EBITTA from −1 to 1 to capture broader range of profitability scenarios. Other explanatory variables are set to their empirical distributions from our full sample of about 1,300 firms (see Appendix 1). For each DTA–EBITTA pair, we compute the expected probabilities of rating downgrades and upgrades. To simplify interpretation, we report the median simulated probabilities and do not consider parameter uncertainty.



Note: The dotted line corresponds to the sample mean EBITTA value.

Figure 1. Median of the simulated probabilities of rating downgrade as functions of DTA and EBITTA (source: authors' calculation based on estimated Model 2 with U (1) and D (0) groups)

Figure 1 presents the median simulated probabilities of a rating downgrade as a function of EBITTA and DTA levels in the previous period. The simulation is based on Model 2 with U (1) and D (0) outcomes (rating upgrades versus downgrades). At the sample's average EBITTA (dotted line), firms with DTA values above 0.75 show over a 60% probability of being downgraded in the next period. Moreover, for certain EBITTA thresholds, the DTA level has little effect on downgrade probabilities, as indicated by the breakpoints in the color scale around DTA = 0. Table 6 reports the minimum EBITTA levels (by DTA) associated with the highest median probabilities of a downgrade.

Table 6. Minimum levels of EBITTA for a given level of DTA and threshold probabilities of downgrades (source: authors' calculation)

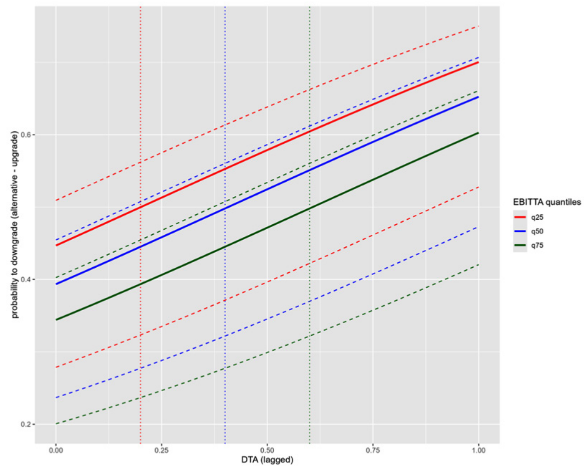
DTA	Highest median simulated probability of a rating downgrade			
	0.2	0.4	0.6	0.8
0.00	0.17	0.04	–0.06	–0.19
0.10	0.19	0.06	–0.05	–0.18
0.20	0.20	0.07	–0.04	–0.16
0.30	0.21	0.08	–0.02	–0.15
0.40	0.23	0.10	–0.01	–0.14
0.50	0.24	0.11	0.01	–0.12
0.60	0.26	0.13	0.02	–0.11
0.70	0.27	0.14	0.03	–0.09
0.80	0.28	0.15	0.05	–0.08
0.90	0.30	0.17	0.06	–0.07
1.00	0.31	0.18	0.08	–0.05

The results indicate that avoiding rating downgrades requires higher profitability to offset higher debt levels. Figures 2 to 4 illustrate this relationship in more detail. They present simulation results from the "U (1) vs D (0)" model with EBITTA fixed at the 25th (0.0226), 50th (0.0514), and 75th (0.1155) percentiles – representing low, median, and high profitability levels, respectively. Each figure shows the median simulated probability of a downgrade (with the 20th and 80th percentiles shown as dashed lines). The dotted vertical lines mark the DTA values where the median probability exceeds 50%, occurring at approximately 0.2, 0.4, and 0.6, respectively.

The median downgrade probability lies closer to the 80th percentile line than to the 20th, indicating an asymmetric distribution. For a typical firm (represented by the sample median), the downgrade risk surpasses 50% when DTA reaches 0.2 and EBITTA is at the 25th percentile. A similar 80% downgrade probability is observed at the same DTA level for firms with median profitability (50th percentile).

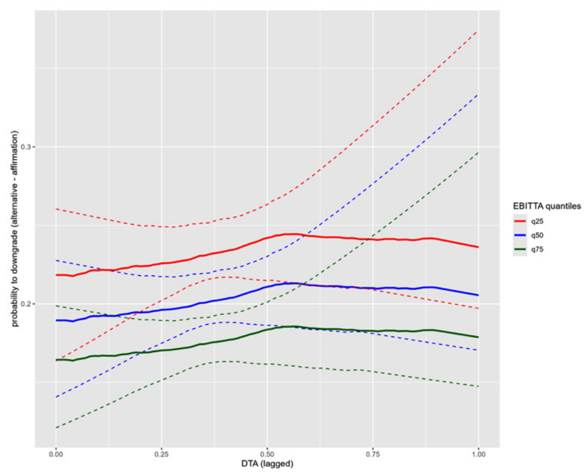
Following the debt capacity concept of Hess and Immenkötter (2014), the debt capacities of low-, medium-, and high-profitability firms (EBITTA below 0.0226, above 0.0514, and above 0.1155, respectively) correspond to DTA levels of 0.2, 0.4, and 0.6. In other words, to shift from a downgrade to an upgrade scenario, debt capacity must increase roughly threefold (from 0.2 to 0.6), while profitability must rise by about five to eleven times. This model includes only U and D categories (excluding unchanged ratings).

For a broader context, the same simulations were also performed for models based on “D (1) vs A (0)” and “U (1) vs A (0)” categorizations, where the alternative to downgrades or upgrades is a rating affirmation.



Note: The solid lines represent the simulated median probabilities. Dashed lines represent the 20% (lower lines) and 80% (upper lines) quantiles of simulated probabilities. Dotted lines correspond to the values of DTA with 50% probability of a rating downgrade.

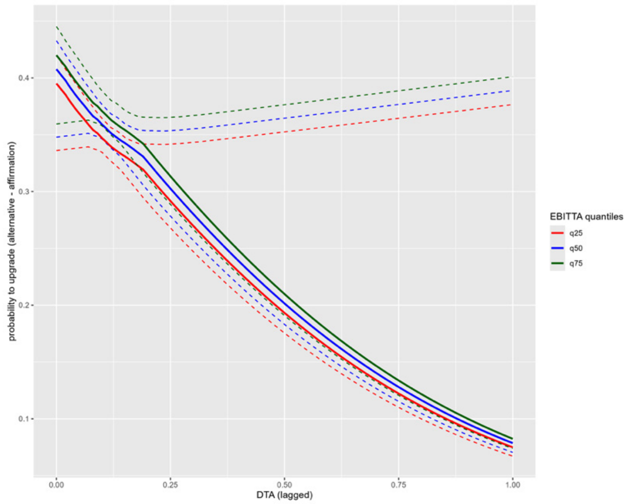
Figure 2. Median of the simulated probabilities of rating downgrades with the alternative of rating upgrades (source: authors’ calculation based on estimated Model 2 with “U (1) and D (0)” groups)



Note: The dotted lines correspond to the sample mean of EBITTA. The solid lines represent the medians of simulated probabilities. Dashed lines represent the 20% and 80% quantiles of simulated probabilities.

Figure 3. Median of the simulated probabilities of rating downgrade with alternative of affirmed rating (source: authors’ calculation based on the estimated Model 2 with “D (1) and A (0)” groups)

When addressing the probability of rating downgrades, the situation differs significantly if the alternative is unchanged ratings. On average (median), an increase in DTA does not significantly change the probability of a rating downgrade. Still, uncertainty increases sharply (more companies have an increased probability of rating downgrades, as suggested by the rising 80% quantile of simulated probabilities of downgrades). Considering the simulation results from the previous model, it follows that for some firms for which the previous model increases the probability of a rating downgrade, their ratings are affirmed (but not upgraded).



Note: The dotted lines correspond to the sample mean of EBITTA. The solid lines represent the medians of simulated probabilities. Dashed lines represent the 20% and 80% quantiles of simulated probabilities.

Figure 4. Median of the simulated probabilities of rating upgrades with the alternative of rating affirmations (source: authors' calculation based on the estimated Model 2 with U (1) and A (0) groups)

Finally, addressing only the probability of rating upgrades, compared with rating affirmations, there is only a low probability of rating upgrades with rising DTA values. Companies' heterogeneity is evident when the DTA is greater than 0.25. We observe that with increasing DTA, there is a share of at least 20% of companies with simulated probabilities greater than 0.3. Thus, owing to their other characteristics, some firms can achieve rating upgrades even at higher DTAs. However, as the median of the simulated probabilities suggests, most firms have a small chance of obtaining a better rating with increasing DTA (differences in their EBIT play only a minor role).

5. Discussion

Among the commonly used specifications of debt capacity in the literature, only two can statistically and significantly explain the changes in a firm's credit rating: DTA (both in lagged form and as change) and EBITInt (only as a lagged variable). Initially, this suggests that the asset-based lending approach (Lian & Ma, 2021) and its changes provide more insight into credit rating changes than cash flow-based lending, as the DEBITDA proxy for debt capacity is insignificant in explaining credit rating changes. To gain insight, we separately control for profitability and collateral aspects using control variables. When we consider the level of debt (in the form of a lagged DTA), profitability only decreases the probability of rating downgrades; however, it does not affect the chances of rating upgrades. Moreover, profitability affects rating changes when the change in debt (DTA change) factors are considered instead of the lagged value (lagged DTA). This indicates that the situation of highly leveraged businesses could be relaxed by high profitability, which represents high internal funds generation ability and lowers potential financial constraints. When addressing upgrades and downgrades alone, compared with rating affirmations, the situation changes. For the probability of a rating downgrade, the DTA in the median of the cases does not significantly change the value of the rating change. However, for debt levels higher than 0.5, uncertainty increases with the variability of the results. Similar results are obtained when analyzing rating upgrades. A significant increase in DTA levels decreases the probability of rating upgrades, where the variability of the data started to diverge when the DTA rose above 0.3. This indicates that other factors (beyond the control variables) play a significant role. However, the rating assessment is only partly based on quantitative data, as it is mostly based on the qualitative aspect of the business.

Nevertheless, our results show that financial constraints moderate the relationship between rating changes, debt levels, and profitability. This is supported by the presence of the financial constraints proxy (SAI), which reaches significant estimates only when modelling rating downgrades. This finding is in line with the literature, as a constrained business cannot reach optimal investment opportunities and cannot follow optimal growth trajectories (Carreira & Silva, 2010), thus affecting the credit multiplier.

With regards to the moderating role of other employed control variables, businesses with high ratings are expected to have little concern about debt capacity and roll-over costs; thus, they can shorten their debt maturity without having to reduce their leverage (Pour & Khansalar, 2015; Lemmon & Zender, 2010; Johson, 2003). Our results support this idea, as the TSIR is significant only when the last rating factor is not considered; if the last rating factor is considered, the TSIR becomes insignificant. However, this effect applies only to rating upgrades. The estimated effect of TSIR is positive even under various model specifications, supporting the findings of Brick and Ravid (1985) regarding the increasing benefits of using debt. We control for debt maturity using the proportion of LTDTD, as this factor seems to contribute to rating both upgrades and downgrades. However, once the industry and last rating factors are incorporated, the debt maturity factors become insignificant, suggesting that the relevant information in the model is being supplemented.

According to Moreno et al. (2018), TSIR represents the relationship between the interest rates of a debt instrument (e.g., bond yields) and different terms or maturities. TSIR is known as the yield curve, which is often shown as a credit spread, that is, the difference between the yield (return) of two different debt instruments that have the same maturity but differ in credit ratings owing to different credit qualities (Chen, 2024). TSIR has three shapes: positive, negative, and flat. A positive yield curve indicates that longer-term bonds are related to higher yields (compared with shorter-term bonds). Conversely, a negative yield curve indicates a negative term structure of interest rates. Our results suggest that under the assumption of a positive TSIR shape, market participants expect robust economic growth and higher future inflation rates. This supports Chen's (2024) findings that a positive TSIR positively affects rating upgrades.

Our findings also support the extant literature on the relationship between corporate and government bond yields (Morris et al., 1998; Leake, 2003; van Landschoot, 2004).

6. Conclusions

Regarding RQ1, our results show that among commonly used debt capacity proxies, only debt-to-total assets (DTA) and, to a lesser extent, interest coverage (EBIT/Interest) significantly explain rating changes.

For RQ2, we find that the effects are asymmetric: debt capacity influences both upgrades and downgrades, while financial constraints and profitability primarily affect downgrades.

We examine how debt capacity and financial constraints influence credit rating changes. Prior work often assumes symmetric effects, yet evidence indicates asymmetry: some factors drive downgrades but not upgrades (and vice versa), risking biased inference. We address this gap by jointly analyzing debt capacity and financial constraints – typically treated in separate literatures – and show that constraint measures, commonly applied to SMEs, also help explain downgrades among large firms. To the best of our knowledge, this is the first comprehensive study linking rating changes with debt capacity and financial constraints.

Our study offers practical insights into rating dynamics. We find that downgrades are moderated by profitability and financial constraints, whereas upgrades are largely unaffected. Profitability's moderating role in debt capacity is limited: highly profitable firms rarely face downgrades regardless of leverage, while firms with severe losses are prone to downgrades even without debt. Moreover, factors influencing upgrades become unclear when debt exceeds 30% of assets, and for downgrades when debt surpasses 50%. Beyond these thresholds, rating changes appear driven by variables such as rollover costs, debt maturity, cash holdings, collateral, and interest rate structure. Results remain robust across specifications.

While our analysis focused on empirical determinants of rating changes, a deeper theoretical explanation of the observed asymmetry was beyond the scope of this paper. Future research could incorporate behavioral finance and managerial decision-making frameworks to explain why firms react more strongly to downgrade risks than to upgrade opportunities. Concepts such as loss aversion or rating-triggered managerial incentives may provide valuable insights into these mechanisms.

Despite our study's theoretical and practical contributions, it has some limitations. First, rating changes or affirmations do not occur frequently, which limits the available observations and increases the uncertainty of the model. Second, the sample size does not allow us to control for the severity of rating downgrades or upgrades; however, in most cases, it was controlled for by one notch. Future research can incorporate additional control variables (unconventional ones) as simulation results show growing uncertainty regarding rating changes when debt levels are higher, thus showing the role of unobserved factors.

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Author contributions

Michal Karas and Daniel Němec conceived the study and were responsible for the design and development of the data analysis. Michal Karas was responsible for data collection. Adam P. Balcerzak and Marek Zinecker were responsible for the theoretical framework and data interpretation. Michal Karas wrote the first draft of the article.

Disclosure statement

Authors declare that they have not any competing financial, professional, or personal interests from other parties.

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APPENDIX

Table A1. Descriptive statistics of selected variables (source: own calculation based on data from Orbis database)

Variable	N	Mean	SD	Median	Min	Max
DTA_1	1302	0.694	0.184	0.696	0.000	1.281
d_DTA	1302	–0.002	0.080	–0.001	–0.567	1.000
SAI	1755	–5.447	1.051	–5.516	–7.708	–2.316
TSIR	1732	2.376	1.446	2.190	–1.550	22.760
ETR_1	1223	0.255	28.479	0.184	–760.133	519.156
d_ETR	1208	–0.346	30.509	0.001	–657.067	648.497
CTA_1	1220	0.077	0.074	0.064	0.000	0.993
d_CTA	1215	0.001	0.057	0.000	–0.920	0.263
FATA_1	1236	0.337	0.288	0.288	0.000	0.992
d_FATA	1230	0.001	0.071	0.000	–0.905	0.821
EBITTA_1	1254	0.054	0.067	0.051	–0.455	0.867
d_EBITTA	1246	–0.007	0.066	–0.001	–0.953	0.493
LTDTD_1	1301	0.655	0.218	0.676	0.000	1.000
d_LTDTD	1301	0.000	0.120	0.000	–1.000	0.947

Note: N represents the number of observations. SD represents the standard deviation.

Table A2. Description of selected factor variables (source: own calculation based on data from Orbis database)

Factor variable	Factors				
Rating change	downgraded	affirmed	upgraded	NA	
	255	886	250	363	
Rating category in the last period	good	near speculative grade	speculative grade	NA	
	178	743	471	363	
Industry (category)	C	G	I	J	M
	489	70	15	120	210

Note: The table describes the number of observations for the corresponding factors.

Table A3. List of variable abbreviations (source: own processing)

Abbreviation	Description
DTA	Debt over total assets
DE	Debt over equity
DEBITDA	Debt over EBITDA
EBITInt	EBIT over interest expense
SAI	size-age index
RDTA	R&D expenditures over total assets
FATA	fixed assets over total assets
EBITTA	EBIT over total assets
GDPpc	GDP per capita [in EUR at current prices]
IND	industry category (NACE classification)
CTA	cash over total assets
TSIR	time structure of interest rates
LTDTD	long-term debt over total debt
ETR	effective tax rate