The Impact of the Dodd Frank Act on the Determinants of Credit Rating Quality

Klumpes, Paul John Marcel; Konstantinos Eleftheriou, Kostas ; Komarev, Iliya; Ronsse, Anne-lise

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ABSTRACT

The *Dodd Frank Act* of 2010 imposed, for the first time, legal liability of credit rating agencies for their judgments, and required public disclosure of rating methodologies. The latter are based on anchoring and adjustment heuristics and are potentially subject to conservatism causing rating agency judgments to shift from risk aversion to loss aversion. Using behavioral decision-making theories, we predict that loss averse rating agencies are likely not to upgrade firms with volatile history of credit rates. We also predict that the loss aversion is mitigated by the passage of the *Dodd Frank Act*. Further, we expect that the process of credit rating anchoring exploits in a more rational way the information about issuing firms' cash-flows, as opposed to the traditional accounting earnings.

Our empirical analysis is based on examining variations in credit ratings for a panel of large US debt issuing firms. Our findings corroborate the behavioral conservatism of rating agencies with regard to the debt issuer's prior credit rating volatility. However, this effect only slightly declines post-*Dodd Frank Act*. Moreover, our findings do not provide consistent support for the expected effect of the Dodd-Frank Act in terms of reliance on cash flow quality rather than earnings quality.

Keywords: Credit rating, Dodd Frank Act, cash flow, accounting quality, risk aversion.

1 Introduction

Credit rating agencies (CRA) claim to use an anchoring and adjustment process in setting and then adjusting credit ratings based on a review of financial statements. However, in the context of criticism of rating agency ratings practices both before and after the financial crisis, whether that process is determined by reference to earnings quality, to cash flow quality, or to other less rational factors remains an unresolved issue. Specifically, we examine the impact of the *Dodd Frank Wall Street Reform and Consumer Protection Act* (hereinafter *Dodd-Frank Act*) which was intended to tighten the regulation of US credit rating agencies. This imposed new regulatory oversight of US credit rating agencies and removed legislative protection regarding their liability against legal action. Previously, a credit rating was an expert opinion provided by a rating agency for a fee on the credit risk of a bond issue, reflecting the probability of default of that bond, and thereby reducing asymmetry between investors and bond issuers (Rhee, 2013). Subsequent to Dodd-Frank Act, the unconditional institutional reliance on this expert opinion was significantly lessened, exposing the individual ratings to both stronger rivalry among agencies and greater requirement for transparent and rational foundations of the credit quality assessment (Huang et al., 2021).

A large body of accounting research has examined the extent to which accounting and or cash flow information impacts professional judgements in many other contexts, such as auditors, bankers, and investment analysts. By contrast, the impact of earnings versus cash flows on credit rating agency decisions has received little attention. Furthermore, credit ratings are important signal for market participants about expert perception of firms' credit risk. The level of credit risk reflected in the credit ratings affects firm's access to funding and their cost of capital (Kisgen, 2006, 2007; Kisgen and Strahan, 2010). Changes in credit ratings are generally followed by market price adjustments (Kliger & Sarig, 2000). However, in the two decades following the collapse of Enron, and in response to criticisms of the efficacy and quality of credit rating processes, US credit rating agencies have faced increased regulatory scrutiny[1]. In the aftermath of the US subprime crisis of 2008, several politicians and economists have voiced concerns about the inability of credit rating agencies to timely and accurately reflect credit and market risks in their rating methodologies[2].

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[1] Following the collapse of Enron, Moody's admitted that the "pace of ratings is too slow to reflect the true nature of credit risk. Subsequently, both Moody's and S&P announced plans to accelerate their ratings practices, conduct more formal reviews and be more specific about how far a rating could fall in the event of a downgrade (Allen ,2020).

[2] See e.g. The Financial Crisis Inquiry Report by the National Commission on the Causes of the Financial and Economic Crisis in the US : https://www.govinfo.gov/content/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf; see also the opinion by Paul Krugman: https://www.nytimes.com/2010/04/26/opinion/26krugman.html?ref=opinion

This is important for several reasons. On the one hand, a turning point in the liability-free US credit rating market consisted in the 2015 regulatory intervention in the credit rating process, whereby a $1.5 billion settlement was made by Standards & Poor's (hereafter" S&P") to the US department of Justice and other litigants (e.g., Calpers), who had raised concerns about the lack of independence from bond issuers and lack of regulatory compliance. Nevertheless, potential conflicts of interest remain for the CRAs to issuing firms, that are based on the user-pays model.

On the other hand, given the monopolistic and underregulated nature of this industry world-wide, it is important to understand what legislation is effective in enhancing the quality and objectivity of the credit rating process. While the S&P credit ratings methodology also evolved from an earnings-based focus towards a cash flow waterfall basis of assessment, questions remain as to whether these changes effectively impacted their assessment of (changes in) the overall credit rating quality of the issuing firm. Baghai et al. (2014) find that, while rating agencies have become more conservative in assigning credit ratings over the period 1985 to 2009, firms and capital markets do not perceive the increase in conservatism to be fully warranted.

This paper provides further insights into this issue, by examining the evolution of credit rating agency sentiment over the two decades since Enron collapse. We draw on prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), which suggests that judgments which are made under conditions of both risk and uncertainty, those losses and gains are evaluated relative to a reference point and that losses loom larger than gains. Despite sentiment being an established and important feature of investment decision making generally (see e.g., DeLong et al., 1990; Shleifer & Vishny, 1997; Baker & Wurgler, 2007) we are the first to examine the behavioral finance aspects of credit rating processes.

These important considerations have attracted little attention from the prior research, which has instead largely focused on "expected versus actual" credit rating influences issuing firms desire for optimal capital structure, based on classical economic foundation related to trade-off or pecking order theories. Extant research assumes that rational behavior by the rated firm drives the credit rating process, i.e., that issuing firms "game" ratings processes through aggressive accounting manipulation and other egregious management devices to manage their "expected credit rating". For example, Hovakimian et al. (2008, 2009) – presume that the firm behaves strategically around an issuer demand-based expected rating model, on the basis that the credit rating agency judgment is a mere "opinion" and not subject to legal litigation. Further, this assumes that credit rating agencies behave "strategically" in setting grades, due to a conflict of interest with issuing firms who pay for their services (Bolton et al., 2012). Prior accounting research is consistent with this assumption. For example, Alissa et al. (2013) examines differences between expected rating and actual rating of firm – they find that accounting manipulations are important for threshold firms. Alissa et al. (2013) build their study on the assumption that company's management is willing to achieve credit rating level in analogy with the target capital structure (Hovakimian et al., 2009). This model assumes that credit rating agencies proceed to a year-by-year ranking of all rated companies where the accounting fundamentals (accrual-based) define the relative ranking of each company in the S&P rating scale. They hypothesize and provide evidence that US sample firms managed their accruals in order to achieve the target credit ranking in this yearly competition.

Jung et al. (2013) extend this research by examining the managerial incentive to manage earnings when firms attempt to achieve a better credit rating. They assume that it is worth managing earnings only for firms in the extremes of a credit rating "notch" (e.g., AA rated firms would not be interested in credit ratings management, but only the AA- and AA+ rated firms). Moreover, instead of focusing on the raw earnings figure as a tool to influence credit ratings, Jung et al. (2013) examine incentives facing US firms to manage the smoothness (volatility) of earnings in time. They measure how "smooth" are the accrual-based earnings with reference to the "smoothness" of cash flow from operations ("smoothness" being proxied by the stand deviation of earnings over the standard deviation of cash flows). However, cash flows are used as a measure of earnings smoothing, not as a factor predicting credit ratings level or changes in ratings.

However, credit rating agencies' methodologies do not mention explicitly the aim to achieve a harmonious ranking of all graded companies. Rating agencies acknowledge instead that after the thorough expert analysis ending with the first issuance of credit rating, each firm's individual rating is reviewed by the assigned analyst at least annually for the need to be up- or downgraded (e.g. see S&P, 2018). Hence, instead of considering overall company rankings, research models exploring determinants and patterns in credit ratings should focus on the determinants of incremental rating changes. Moreover, the very concept of target credit rating introduced by Hovakimian et al. (2008) by analogy with the target capital structure is debatable, especially when modelled via accrual-based accounting variables that are themselves impacted by accrual management creating thereby a recursive loop between target rating and target accruals.

Frost (2014) notes that there is currently little evidence available to support the criticisms of the competence and value of credit rating agencies in the light of the apparent conflicts of interest with their credit issuing firm clients. Our study aims to contribute to this literature by providing answers to the following questions: Do behavioral factors associated with behavioral biases (conservatism, loss aversion) drive the credit rating agencies' judgments to make and then subsequently change issuers' rating? Furthermore, did the passage of the *Dodd Frank Act* cause a change in whether rating agency quality judgments to be associated each with either accounting or by fundamental cash flows of the credit issuing firms?

Furthermore, prior research has generally assumed that credit rating processes are impacted primarily through accounting-based earnings metrics and manipulations. By contrast, we are the first to develop and test a "cash waterfall" of cash-based metrics for assessing the quality of cash flow, by introducing a "cash available to repay debt" metric which complements the "net operating cash flow" metric cited in prior research. This enables us to examine whether credit rating grading is related to real cash flow quality.

In this paper we propose an alternative approach to those used by Jung et al. (2013) and Alissa et al. (2013). First, we relax the assumption in Alissa et al. (2013) that credit ratings are set year-by-year, independent of the rating in the prior period. To do this, we examine determinants of changes in credit ratings between investment and speculative grades, not determinants of relative ranking between companies each year. Second, we introduce cash flow measures as basic metrics for companies' credit risk and test their capacity to predict changes in credit ratings. For instance, the S&P puts clearly the emphasis on cash flow as a fundamental intrinsic metric for credit risk, whereas other performance metrics are considered as contextual for further adjustments.

Moreover, we develop hypotheses concerning the importance of loss aversion of CRAs when ranking issuing companies, and the change of this importance after a regulatory intervention aiming to rationalize and clarify rating methodology. This enables us to examine the impact of the introduction of the *Dodd-Frank Act* on both the earnings versus cash flow quality of credit ratings and the importance of past credit rating uncertainty (proxied by rating volatility) on current year ratings. We predict that credit ratings were more strongly impacted by rating uncertainty in the period before as compared to the period after the passage of the *Dodd Frank Act*. We also predict that ratings of issuing firms were influenced by earnings (cash flow) quality in the period before (after) the passage of the *Dodd Frank Act*. To test these hypotheses, we use a sample of issuing firms over the period 2002-2017. Our findings are generally consistent with the predictions about changes of credit rating grades, but not consistent with predictions about variations of credit rating grades after the regulatory changes. These findings bear on the relative and incremental salience of behavioral biases in estimating credit quality of debt issuing firms, on the one hand, and on cash-based versus earnings-based determinants of rating quality, on the other hand.

The rest of this paper is organized as follows. Section 2 provides the institutional background to the study with a brief chronological outline of the evolution of credit rating agency regulation over the 2 decades after the collapse of Enron. Section 3 develops the hypothesis. Section 4 overviews the research method used to test the hypotheses. Section 5 presents the results. Finally, section 6 provides discussion and conclusion.

2 Institutional Background

This section provides institutional background as to the potential impact of regulatory interventions on the sentiment of credit rating agencies. Table 1 summarizes the key timeline of phases of regulatory intervention in the decade following the demise of Enron.

INSERT TABLE 1 ABOUT HERE

The four major events which potentially impacted S&Ps credit rating began with the post-Enron introduction of the *Sarbanes Oxley Act 2003* (SOX). SOX prohibited the provision of most types of non-audit services by audit firms to their clients. Subsequently the SEC issued *Rule No. 33-8183* (SEC 2003) which prohibited audit partner compensation that rewards the sale of non-audit services to their clients. This rule was created in response to the SEC Following heavy criticism of practices of statutory auditors in failing to detect accounting fraud leading to the collapse of Enron.

The role of the credit rating agencies in relation to the bankruptcy of Enron in 2001 was also heavily criticized. SOX required the SEC to provide a report, within 18 months concerning the role of credit rating agencies in securities markets. The SEC report (2004) found that there were several deficiencies in the rating process and conflicts of interest. However, the industry avoided regulation by claiming that their rating process was not a legally binding process. Despite this, internationally the International Organization of Securities Commissions (IOSCO) issued several high-level principles that credit rating agencies could follow concerning their code of conduct, based on a "comply or explain basis". The first IOSCO principle – quality and integrity in the rating process – is given effect in the regulatory programs through, for example, explicit requirements on credit rating agencies that were given Nationally Recognized Statistical Rating Organization (hereinafter NRSRO)[3] status to adopt, implement and enforce measures to ensure that credit ratings are based on a thorough analysis of all available and relevant information and that the information they use in developing credit ratings is of sufficient quality and from reliable sources.[4] The regulatory programs reviewed also give effect to the first principle through provisions that implicitly mandate measures designed to promote quality ratings by providing authority to the supervisor to deny or revoke the registration of, or to impose remedial measures on, a CRA that does not have adequate financial and managerial resources to consistently produce credit ratings with integrity.

The second principle – independence and conflicts of interest – is given effect in the regulatory programs through, for example, provisions that require a CRA to implement procedures designed to identify and eliminate conflicts of interest inherent in its business activities. It also requires a CRA to manage and publicly disclose to the market the conflicts of interest inherent in its business activities.

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[3] Hereafter, Credit Rating Agency (or CRA) and NRSRO are used interchangeably.

[4] The use of the term NRSRO began in 1975 when the SEC promulgated rules regarding bank and broker-dealer net capital requirements. The single most important factor in the Commission staff's assessment of NRSRO status is whether the rating agency is "nationally recognized" in the United States as an issuer of credible and reliable ratings by the predominant users of securities ratings. Several commentators criticised this assignment as a "government sanction" (e.g., Surowiecki, 2002). following criticism that the SEC's "No Action letter" approach was simultaneously too opaque and provided the SEC with too little regulatory oversight of NRSROs, the U.S. Congress passed the Credit Rating Agency Reform Act of 2006, which required the SEC to establish clear guidelines for determining which credit rating agencies qualify as NRSROs.

Subsequently, the Congress passed the *Credit Rating Agency Reform Act of 2006*, which obliged credit rating agencies to disclose publicly description of their procedures and methodologies, and to provide the SEC with audited financial statements. It furthermore prohibited CRAs from issuing credit rating for an entity that provided the CRA with a material percentage (10%) of tis total net revenue, and obligated CRAs to disclose conflicts of interest.

Subsequently, the SEC also issued a rule (38 and 4, SEC 2008) which required investors to undertake an "independent analysis" when buying corporate debt, instead of just relying on credit rating agency opinions. Emphasizing the importance of judgment in influencing credit rating decisions, credit rating agencies defended themselves against investor allegations of fraud or negligent misrepresentation by resorting to seeking protection under the First Amendment to the US Constitution, which protects freedom speech.

Following further criticism of the role of credit rating agencies in facilitating the financial crisis of 2008, Congress passed the *Dodd Frank Act* of 2010, which imposed several new regulatory interventions in the activities of credit rating agencies. This included the creation of an Office of Credit Ratings, which is empowered to conduct yearly review of NRSRO credit rating methodologies, as well as other requirements related to ensuring continuing professional education and attaining specified training standards. Crucially, it removed the previous legislative protection regarding NRSRO's liability against legal action. Previously, their products were considered to be mere "journalistic opinions", unreservedly protected by the *First Amendment* (Cash, 2019). Subsequently, the SEC issued a rule obliging NRSROs to establish, monitor and enforce internal controls on all aspects of their business.

Finally, in 2015, the S&P settled a case initiated by the US Federal Department of Justice into deficiencies in its credit rating processes. This resulted in the payment of a USD 1.7b settlement fine, and a pledge by S&P to strengthen its independence from issuer influence, improve its credit rating methodology and enhance their regulatory compliance and analytical quality. [5]

Subsequently, S&P also upgraded their rating methodology documentation in 2015 which, for the first time, cited a "waterfall of cash flow" approach in determining their assessment of the corporate bond issuer quality. Previously, the S&P methodology had emphasized earnings quality (S&P had issued the "core earnings" concept in 2003), this was subsequently removed as a variable from S&P Compustat database in 2008.[6]

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[5] Another large rating agency, Moody's, was also subject to litigation and subsequently settled with the Department of Justice and other litigants in 2017 for USD864 million (Friefeld, "Moody's Pays USD864 million to US, States, over Pre-Crisis Ratings" Business News, 31 January 2017.

[6] There is conflicting evidence as to whether S&P Core earnings is more useful than standard GAAP-based earnings for investors (e.g. Robinson et al., 2008; Rouen et al. 2021).

There have been relatively few studies which specifically examine the effectiveness of the regulatory interventions. Boylan (2012) identifies unconscious bias as a potential source of inaccuracy in the credit ratings process. Whereas he finds that the *Dodd Frank Act* is effective in curbing intentional decisions to comprise ratings, it does not adequately address relevant structural issues associated with unconscious biases in judgments underlying credit ratings. He concludes that further changes need to be made to credit rating agencies' fee structures, business models and risk management functions.

3 Development of Hypotheses

This section develops hypotheses regarding the determinants of both the initial setting and the subsequent adjustments of credit ratings prior to and after the passage of *Dodd Frank Act*.

Our first hypothesis concerns whether the criteria used by rating agencies to rate nonfinancial corporate debt issuers are influenced only by rational adjustments to financial and accounting fundamentals of the issuer, or alternatively are opinions impacted by the agency's perception of the riskiness of grading the issuer.

Unlike the common investor, a rating agency has access to private information pertaining to debt issuers. Its role is to make this information publicly useful through the issuance of a summary credit rating. However, like common investors, the processing of privately available information by the rating agency staff is not free from behavioral biases. According to the anchor-and-adjustment rating process publicized by S&P, an initial credit score is computed for each debt issuer by using an undisclosed mathematical model which incorporates some fundamental financial and strategic variables (S&P, 2014; S&P, 2018). Subsequently, based on this anchor, an adjustment is made so as to take into account idiosyncratic, qualitative characteristics of the debt issuer (diversification, financial policy, management & governance, benchmark with comparative firms…). These subsequent adjustments, made by expert-analysts, are prone to behavioral biases. Prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) explains deviation of individual's decisions from expected rational patterns predicted by utility theory by a range of behavioral biases, such as: loss aversion, risk seeking, framing, heuristics, anchoring, endowment, hindsight bias... With regard to credit ratings, prospect theory predicts that individual adjustments to the credit rating for each debt issuers represent a subjective process which may be significantly impacted by the past negative experience that the agency has with a specific issuer (see e.g., Ayres and Dolvin, 2021).

Hence, we expect that firms with unstable financial fundamentals and therefore highly volatile past ratings are seen as (1) providing inconsistent signals as to their financial stability and (2) perceived as being subject to greater default risk. The firms that are subject to high volatility in their rating quality represent higher risk of mistake and therefore higher loss for the rating agency, as compared to firms exhibiting more stable credit quality over time. In other words, debt issuers with relatively stable credit rating history are considered less risky by the CRA and therefore are more likely to be ranked as investment grade. On the opposite, issuers with highly volatile past ratings induce a sense of insecurity in the loss-averse[7] rating agency and are more likely to be ranked as speculative grade quality.

H1a: Ceteris paribus, for US nonfinancial debt issuing firms, the increases of prior year credit ratings volatility negatively affect the CRAs propensity to assign investment quality credit rate in the current year.

Among other actions, the *Dodd Frank Act* increased legal liability for CRAs issuing inaccurate rating decisions, in a manner similar to a statutory audit firm issuing inaccurate audit opinion. The move away from the opinion-based credit ratings to rational ratings based on more transparent conceptual foundations should lead to lower impact of behavioral biases in the credit rate setting process, such as the loss aversion predicted in the previous hypothesis. We therefore predict that the strength of the association between the rating grade and the volatility of the rating over the past years will be weaker in the period following the passage of *Dodd Frank Act*.

H1b: Ceteris paribus, for US nonfinancial debt issuing firms, the negative effect of prior year credit ratings volatility on the propensity of CRAs to assign investment quality credit rate in the current year is weakened after the passage of Dodd Frank Act.

Our second hypothesis concerns whether the anchoring of a firm's credit rating grade quality is primarily associated with either earnings or cash flow determinants. The two waves of post Enron and financial crisis regulatory interference in the credit rating industry resulted in (i) post-Enron, a move away from statutory based GAAP earnings towards a core earnings period and (ii) an explication of more detailed credit rating methodology post the financial crisis to reflect a "cash waterfall" approach. It is therefore expected that CRAs have used accounting earnings as a primary basis to anchor the rating before the *Dodd Frank Act*:

H2a: Ceteris paribus, the propensity to assign investment grade credit ratings to US nonfinancial debt issuing firms is positively associated with firm earnings in the period before the passage of Dodd Frank Act, and is not significantly associated with firm earnings in the period after the Dodd Frank Act.

One of the purposes of *Dodd Frank Act* was to improve the quality of credit rating agency methodologies by imposing regulatory oversight. It is therefore expected that cash flow data is used as a primary basis to set the anchor for the credit ratings after the passage of the Dodd Frank Act:

[7] It is understood that losses to which rating agencies are exposed can be both financial (litigation settlements to investors and regulators) and non-financial (reputational loss).

H2b: Ceteris paribus, the propensity to assign investment grade credit ratings to US nonfinancial debt issuing firms is positively associated with firm cash flows in the period after the passage of Dodd Frank Act and is not significantly associated with firm cash flows in the period before the Dodd Frank Act.

4 Research method

Sample selection procedures, data sources, variable definitions and model specifications are presented in this section.

4.1 Sample selection procedures

The sample is based on large US firms that were listed on either the New York Stock Exchange or NASDAQ in the relevant period in the sixteen years following the bankruptcy of Enron in 2001, study and which meet the following criteria: (1) the firms were continuously listed in the S&P 500 index for the entire study period and were not subject to mergers and acquisitions activity. (2) financial firms were excluded. (3) S&P ratings data and relevant financial information is available for all firms for at least 5 years before the start of the sample period in order to compute the standard deviation of credit rating variable.

4.2 Data and data sources

Data is sourced from Compustat and includes both annual credit rating data and financial data for 430 companies over a period of 16 years, from 2002 to 2017.[8] The sample constitutes an unbalanced panel of 6,846 company-year observations.

Table 2 summarizes the ratings grade of the sample credit issuing US firms, by year. As shown in Table 2, the sample is unbalanced in the final three years of the study period.

INSERT TABLE 2 ABOUT HERE

Figure 1 shows the trend of the number of sample of firms graded either at investment, threshold, or speculative credit grade quality. There is a significant decline in the number of investment grade firms over time, especially after 2010 suggesting increasing conservatism in grading after the passage of the *Dodd Frank Act*.

[8] Eighteen firms of this sample were subject to merger, acquisition or were delisted from the NYSE or NASDAQ after 2014. Section 6 discusses survivorship bias.

INSERT FIGURE 1 ABOUT HERE

4.3 Empirical Specifications

We examine in this section two alternative models representing the driving forces behind the decision of a CRA to change the rating of a debt issuer. The first model is consistent with Hovakimian et al. (2008) and Alissa et al. (2013) credit rating models which use accounting accruals and accrual-based earnings as rating quality predictors. Such a model is also consistent with the premise that firms can use accounting accruals to manipulate credit ratings (e.g. Alissa et al., 2013; Jung et al., 2013) The independent variables in these models reflect the understanding that the accounting accruals reflect not only the current but also long-term cash generating capacity of the firm, considering that the accrual-based earnings will be converted into cash over the current and the future accounting periods.

Our second model is an adaptation of the classical earnings model where accounting profits and volatility of earnings are replaced by cash flow from operations and variability of cash flows, respectively. In addition, a measure of total cash and cash equivalents is added among the regressors as a proxy for the "cash waterfall" effect. The cash-based determinants of credit ratings are drawn from the definition of credit risk as the capacity of a firm to repay its immediately maturing liabilities. Hence changes in the cash stock and the cash flows variables should lead to adjustments in credit ratings.

To test the above models, we use a probit estimation, defined as follows:

$P[RATE \leq j|X] = N(k_j - X'\nu)$, where j = 1, 2, 3; N(.) – is the standard normal cumulative distribution function; k_j and $\nu_{(k\times1)}$ are unknown parameters. With *RATE* representing the categories of credit grades in the S&P rating scheme defined as 1= Investment grade (firms rated A to BBB+), and 0 = Speculative grade otherwise (firms rated BB+ and below).

Further, *X(.)* is defined by three alternative specifications:

(I) Earnings Model:

$$X_1 = a_0 + \alpha_1 SDCR + \sum_1^j \mathrm{A}_i + \sum_1^l \mathrm{B}_i + \sum_1^m \Delta_i + \varepsilon_1$$

(II) Cash Flow Model:

$$X_2 = a_0 + \alpha_1 SDCR + \sum_1^j \mathrm{A}_i + \sum_1^l \Gamma_i + \sum_1^m \Delta_i + \varepsilon_1$$

Where,

SDCR = volatility of credit ratings.

A - vector of standard credit rating determinants, according Hovakimian et al. (2008) including *MTB*, *TANG, RDIND, SGA, SIZE* (see definitions below).

B - vector of earnings-based credit rating determinants, including the following variables *PROFIT*, *OPRISK* (see definitions below).

Γ - vector of cash flow-based credit rating determinants, including *OPCFO, CFO*, and *CHETA* (see definitions below).

Δ - vector of variables controlling for the industry fixed effects, clustered into mining, manufacturing, utilities, and retail (Fama and French, 1997).

4.4 Variable definitions

The following variables are defined for the purpose of testing the empirical hypotheses:

- *Dependent variable*

RATE, categories of credit grades in the S&P rating scheme defined as 1= Investment grade (A to BBB- rates), and 0 = Speculative grade (BB+ rates and below)

- *Independent variables*

SDCR, volatility of credit ratings, proxied by the standard deviation of rating over prior five years.

MTB, the ratio of a firm's market value of assets to total assets, where the market value of assets is total assets minus book equity plus market equity.

TANG, the ratio of a firm's net property, plant, and equipment to total assets.

RDIND, a binary variable set equal to one if a firm has non-missing RD and zero otherwise.

SGA, the ratio of a firm's selling, general, and administrative expenses to sale.

SIZE, the natural logarithm of sales.

PROFIT, the ratio of a firm's operating income over lagged total assets.

OPRISK, the standard deviation of a firm's operating income scaled by lagged total assets over the previous five fiscal years.

CFO, cash flow from operations.

OPCFO, the standard deviation of a firm's net operating cash flow scaled by lagged total assets over the previous five fiscal years.

CHETA, the total of cash and cash equivalents over total assets.

All explanatory variables are winsorized at the 1% level.

5 Empirical tests

Firstly, this section provides univariate statistics for all variables of interest. Further, the estimations of the two baseline empirical models are presented. Finally, we present series of robustness tests.

5.1 Descriptive statistics

Table 3 provides descriptive statistics of the main variables defined in section 4.4.

INSERT TABLE 3 ABOUT HERE

The univariate statistics in the above table suggest that the variables used in the empirical tests are characterized by sufficient ranges of variability. Moreover, the ranges of variability are maintained in both periods before and after the *Dodd-Frank Act* (panels B and C). Most of the variables have similar measurement scales which should simplify the readability of results.

5.2 Probit test results

This section reports probit model estimations used to test our hypotheses concerning the determinants of credit rating quality upgrades. We separately report the earnings model to tests hypothesis 2a (table 4) and the cash flow model to test hypothesis 2b (table 5). On the other hand, hypotheses 1a and 1b are tested via the variable *SDCR* used in all models. Each table displays the results of probit estimations conducted for both the full sample period, and the two sub-periods before and after the passage of the *Dodd Frank Act*.

INSERT TABLES 4 and 5 ABOUT HERE

Since the probit estimation assumes non-linear relations between the dependent and the independent variables, the estimated regression coefficients reflect only the direction of the interaction but are less useful as to the direct interpretation of the magnitude of this interaction. Consistent with the econometric literature, we compute and report marginal effects to provide basis for interpretation equivalent to the coefficients of an ordinary least square estimation (see e.g., Green, 2003). The marginal effect of an independent variable indicates the percentage increase in the probability of switching between the two credit rating categories – speculative to investment – caused by a one-percent increase in the independent variable under consideration.

Both tables 4 and 5 show negative and statistically significant effect of the volatility of prior year credit ratings (*SDCR*) on the propensity of the CRA to assign investment quality rate in the current year. Moreover, although statistically significant, the magnitude of this effect is reduced in the period after the passage of *Dodd Frank Act* (marginal effect of -0.053, for both the earnings and the cash flow models), compared to the period before the reform (marginal effect of -0.085, for both the earnings and the cash flow models). These results provide strong support for hypothesis 1a and some support for hypothesis 1b.

By contrast, the results in Table 4 provide only equivocal support for hypothesis 2a. For the entire sample period, there is a positive and statistically significant effect of the profitability of the issuer (*PROFIT*) on the probability to be upgraded to investment quality rate (marginal effect of 0.337). Nevertheless, this effect is insignificant for either one of the two sub-sample periods. This may be due to several structural breaks happening in years other than the year of passage of *Dodd Frank Act*, and which revert the sign of the association between *PROFIT* and *RATE*. Furthermore, *OPRISK* is not significantly associated with investment quality upgrades in any of the sample periods.

Table 4 also shows that both *SIZE* and *SGA* are positively related with investment quality upgrades for all sample period tests. By contrast, the rest of the control variables have more inconsistent relationships with credit rating upgrades. Both *MBT* and *TANG* exhibit positive statistically significant associations with upgrades to investment credit rating quality in the overall sample period, but not for the subperiods before and after the *Dodd Frank Act*.

Table 5 shows that cash flow from operations (*CFO*) is positively and significantly associated with the probability of a debt issuer to be upgraded to investment quality rate, for both the entire sample period and for each of the subperiods pre- and post- the passage of the *Dodd Frank Act*. However, the statistical significance of this relationship decreases from 1% in the period before the reform, to 10% in the period after the reform. These results are contradicting the predictions of hypothesis 2b. Nevertheless, *OPCFO* is not statistically associated with credit rating quality upgrades, whereas *CHETA* exhibits significant and positive impact on the probability to be rated as investment quality only in the period after the regulatory reform. The latter association bears some support, although partial, to hypothesis 2b.

Among the control variables in table 5, only *SIZE* is positively and significantly associated with credit rating quality upgrades for all three periods. Consistent with the results of the earnings model, table 5 confirms that both *TANG* and *MTB* are positively and significantly related to credit rating quality upgrades for both the entire sample and for the pre- and post-*Dodd Frank Act* subsample periods. By contrast, *SGA* is only positively and significantly associated with credit rating quality upgrades only in the sub sample periods, but not for the entire sample. Finally, *RDIND* is negatively and significantly associated with credit rating quality upgrades only in the pre-*Dodd Frank Act* subsample period.

5.3 Robustness tests

This section summarizes the results of several robustness tests undertaken to validate the findings of the baseline probit models reported above.

5.3.1 Sensitivity to ratings grade quality

Our underlying premise in the baseline probit model, consistent with prior research, is that the credit rating grade quality is proxied by whether the rated firm has issued debt that is either investment grade quality, or speculative grade quality. It could well be that there are more nuanced variations in the determinants of credit rating quality within each of these grade categories. For example, prior research suggests that earnings manipulation incentives are higher for firms on the threshold than those whose debt is rated as either investment or speculative grade quality (e.g., Brown et al., 2015).

To obtain some intuition into the impact of this recategorization of credit rating quality, Figure 2 plots the trends over time in the standard deviation of yearly accounting returns for sample firms in each of the three quality grades: investment, threshold, speculative. Consistent with an earnings management explanation, before the financial crisis of 2007, the standard deviation of accounting returns over the previous five years is higher for threshold credit rate graded sub-sample firms than for either investment or speculative grade sub-sample firms. However, after the financial crisis, the earnings variations within speculative grade sub-sample firms are consistently higher than either threshold or investment grade firms. This finding provides some intuitive support for our predictions.

INSERT FIGURE 2 ABOUT HERE

We therefore replace the binary variable *RATE* used in the probit model with an ordinal categorical variable *RATE'* which takes the values of 3 for investment grade (firms rated A to AAA), 2 for threshold grade (firms rated BBB- to BBB+), and 1 for speculative grade (firms rated BB+ and below), according to the S&P credit rating quality scheme. Tables 7 and 8 report the results of the ordinal probit model tests where *RATE'* is used as a dependent variable.

INSERT TABLES 6 and 7 ABOUT HERE

These results are mostly consistent with those reported in the previous section. One can notice that in both tables 6 and 7 the marginal effects of all independent variables are always of the same sign for both the threshold and the investment grade firms. This suggests that S&P does not exhibit greater risk aversion toward debt issuers on the threshold but applies the same principles and methods when grading threshold and investment quality firms.

For both the earnings model (Table 6) and cash flow model (table 7), we observe consistently negative and statistically significant effects of the volatility of prior years' grades (*SDCR*) on the propensity of the firm to be graded as either threshold or investment quality. This confirms our previous finding supporting the prediction of hypothesis 1a. That is, the prior year volatility in the rating grade of the issuer, proxy for credit rating agency loss aversion, is a statistically significant determinant of overall the credit rating grade quality. Nevertheless, the results do not support the expectation that the loss aversion of the rating agency has declined after the passage of *Dodd Frank Act* – the marginal effects of *SDCR* on *RATE'* are slightly stronger for the period after the reform – thus rejecting hypothesis 1b.

Furthermore, there are some contradicting results regarding the relationship of credit rating quality and demand side factors. Both *PROFIT* (hypothesis 2a, table 6) and *CFO* (hypothesis 2b, table 7) are significantly and positively related to the ordinal credit rating variable *RATE'* for both the overall sample period and the pre-*Dodd Frank Act* sub-period, but not for the post-*Dodd Frank Act* sub-period. The negative association between *PROFIT* and *RATE'* in the pre-*Dodd Frank Act* sub-period which fades the subsequent period (table 6) supports the predictions of hypothesis 2a. Nevertheless, the same pattern of relationship between *CFO* and *RATE'* strongly contradicts hypothesis 2b (table 7). In addition, both risk proxies *OPRISK* (table 6) and *OPCFO* (table 7) are negatively associated with *RATE'*, yet only for the period after the Dodd Frank Act. This is mostly true for the case of speculative and investment grade ratings, whereas the marginal effects are less significant for threshold grade ratings.

There are also some further clarifications as to the effect of various control variables on credit rating quality changes. As expected, *MTB*, *TANG* and *SIZE* are positively associated with credit rating quality upgrades for both earnings and cash flow models (except for the sub period after the passage of the *Dodd Frank Act* for the cash flow model). By contrast, both *RDIND* and *SGA* (for the latter, except for the period prior to the passage of the *Dodd Frank Act*) are not significantly related to credit rating quality upgrades, for both earnings and cash flow models.

5.3.2 Moodys v S&P credit rating quality

The empirical tests reported in the previous section are based exclusively on S&P credit ratings, but not on ratings issued by the other two major US NSRO, Moody's and Fitch.[9] There is conflicting evidence on the convergence of the rating methodologies and the resulting credit quality rates issued by the three major US rating agencies. Based on the relative impact of Moody's and S&P on bond yields, Livingston et al. (2010) find that investors differentiate between the two ratings and assign more weight to Moody's ratings, probably because the latter have become more conservative after 1998. By contrast, Caridad et al. (2020) report convergence of ratings between S&P and Moody's in the subsequent period 2014-2018, notwithstanding discrepancies in certain economic sectors and the choice of ratings scales. It could therefore be possible that the credit ratings methodology employed by Moody's differs substantially from that of S&P, and in consequence the supply side related determinants of credit rating quality can materially differ.

Based on the analysis of ratings provided by both S&P and Moody's, we identified that 80% of our sample firms rated by S&P are also rated by Moody's. This results in a revised subsample of 357 firms graded by both CRAs. For this subsample we test our research hypotheses by using Moody's credit ratings. Figure 3 reports the variations in ratings grade, both in terms of the average (Panel A) and the standard deviation of ratings grade over the preceding five years (Panel B).

INSERT FIGURE 3 ABOUT HERE

Figure 3, panel A shows that the average S&P grade for the sample firms is consistently higher than that of Moody's over the entire study period, consistent with the findings of Livingston et al. (2010). By contrast, figure 3 panel B shows that, while the standard deviation of Moody's credit ratings was mostly higher than that of S&P in the early period 2002-2008, they converged after the 2009. This is consistent with the finding of the Caridad et al. (2020) study.

Tables 8 and 9 report probit model estimations using Moody's credit quality rates for the earnings model and the cash flow model, respectively. Since 73 sample companies do not have Moody's grade, the sample was

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[9] There are three major US credit rating agencies which dominate the market for credit rating services: S&P, Moody's and Fitch. Of these, both S&P and Moody's were subject to political and legal scrutiny as to the quality of their credit rating methodologies, and both settled litigations in 2015 and 2017, respectively. By contrast, Fitch, which is a relatively smaller rating agency, did not face any legal scrutiny. Furthermore, their credit ratings are not publicly available, and cover only a small subset of the S&P 500 firms. We therefore excluded Fitch from the additional analysis reported in this section. The findings reported in this section are therefore subject to this caveat.

reduced to a total of 5683 observation over the entire period. The independent variable here is *RATE"* taking the value of 1 when the debt-issuing firm is rated as investment grade by Moody's, and 0 otherwise.

INSERT TABLE 8 ABOUT HERE

Upgrades in Moody's credit quality rates are statistically negatively associated with *SDCR*, for both the earnings and cash flow probit models, and for all sample periods. This result is consistent with the findings reported for the larger S&P sample in tables 4 and 5 and thus supports the predictions of hypothesis 1a. Moreover, the lower in magnitude and less significant marginal effect of *SDCR* in the period post-*Dodd Frank Act* provides some support for hypothesis 1b. Although present, the impact of risk aversion on credit rating upgrades by Moody's fades after the passage of *Dodd Frank Act*.

Table 8 reports consistent results between the two credit rating agencies regarding the predicted positive effect of earnings on credit rating upgrades. The marginal effect of *PROFIT* on upgrades to investment quality rates is positive and statistically significant for both S&P and Moody's grades for the entire sample period and insignificant for the two subperiod before and after the *Dodd Frank Act*. A partial exception to this is the fact that the effect of PROFIT on Moody's ratings upgrades is slightly significant (at the 10% rate) in the period after the passage of *Dodd Frank Act*. This suggests relative consistency in rating methodologies between the two major agencies as regards the relevance of accounting earnings. Therefore, these results provide partial support for the predictions of hypothesis 2a.

Table 8 also shows some consistency in the effects of most of the control variables on credit rating quality upgrades for ratings issued by Moody's and S&P. This concerns the variables *MTB*, *TANG*, *SGA*, *SIZE* and *OPRISK*. Only minor discrepancies appear with regard to *RDIND*, which coefficient is positive but statistically insignificantly when using Moody's credit quality grades.

INSERT TABLE 9 ABOUT HERE

Similarly, Table 9 shows important similarity between the two rating agencies regarding the association between cash flow and credit rating grade quality.

For both S&P and Moody's, *CFO* exerts positive and statistically significant impact on rating quality updates in the entire period. However, in contrast to the findings reported in Table 5 for the larger S&P sample, the statistical significance of the regression coefficient of *CFO* in the Moody's subsample increases from 10% to 1% in the period after the passage of *Dodd Frank Act*. This result provides greater support for the expectation in hypothesis 2b, suggesting that Moody's rating methodology might have been more strongly impacted in the right direction by the legislative reform. The difference in rating methodologies post-*Dodd Frank Act* is confirmed by the negative but statistically insignificant effect of *CHETA* on rating quality upgrades by Moody's for all sample periods (table 9). Whereas table 5 is reporting positive and statistically significant effect of *CHETA* on credit rating upgrades in the post-*Dodd Frank Act* period.

Nevertheless, table 9 also shows that, *OPCFO* exerts negative but statistically insignificant effect on rating quality upgrades for Moody's ratings and in all sample periods. This result is consistent with the one obtained with the S&P credit ratings.

Other control variables also show consistent statistically significant impact on credit rating upgrades for both the Moody's subsample (table 9) and the larger S&P sample (table 5). This concerns *MTB, SGA,* and to some extent *TANG* and *SIZE*. Whereas *RDIND* exhibit some important discrepancies between the methodologies of the two CRAs. Namely, this variable appears to have positive but strictly insignificant effect on rating upgrades in the Moody's methodology and negative and significant effect in the S&P methodology, especially in the period before the *Dodd Frank Act*.

All in all, the results of the probit estimations using Moody's credit ratings data do not diverge significantly from those obtained with S&P data.

5.3.3 Control for Endogeneity Bias

Several regressors in our models, such as *SIZE*, *TANG*, *PROFIT*, may be reversely and simultaneously associated with the dependent variable. While using panel-data, one practical way to verify the robustness of our results to potential endogeneity bias is to use lagged values of time-variant regressors. Indeed, past values of regressors are not biased by potential reverse reaction of the dependent variable (see e.g. Coles et all., 2006 using lagged regressors to control for simultaneity bias).

Tables 10 and 11 report the results of probit tests of the baseline earnings and cash flow models using one-year lagged values for all independent time-variant variables.

INSERT TABLE 10 ABOUT HERE

Regarding the endogeneity-controlled earnings model in Table 10, one can notice very similar results with those reported in Table 4. That is, the lagged measures of *SDCR, MTB, TANG, SGA, SIZE*, and *PROFIT* play significant roles in determining the current-year value of *RATE*. Nevertheless, *L.PROFIT* exhibits positive statistically significant effect on *RATE* even in the period after the passage of *Dodd-Frank Act*.

INSERT TABLE 11 ABOUT HERE

The endogeneity-controlled cash flow model in Table 11 confirms once again the significant effect of the volatility of credit ratings on their current level upgrades. Il also corroborates the significance of other core determinants, *MTB*, *TANG*, *SGA*, and *SIZE*. Moreover, the model corroborates the positive and significant effect of the lagged *CFO*, but also the negative and significant effect of the lagged *OPCFO* for both periods before and after the passage of *Dodd-Frank Act*. Like the initial results, the lagged value of *CHETA* exhibits significant influence on *RATE* only in the period after the *Dodd-Frank Act*.

5.3.4 Survivorship Bias

Because the development of an empirical proxy for fluctuation of credit rating grade quality requires the sample firm to be in existence for five years prior to the current year, our sample selection procedures are potentially subject to survivorship bias. We screened out a minority of the sample firms which did not survive for the last three years of the sample period, i.e., after 2014. This resulted in a holdout subsample of 18 firms which were either subject to takeover, delisting or bankruptcy after 2014. We performed all the test with this subsample, which yielded very similar results. Nevertheless, having only 41 observations with speculative grade non-surviving firms - the least frequent category of our dependent variable – that is, less than 4 observations per regressor, the results of these tests are not sufficiently robust to be reported here.

6 Discussion and Conclusion

Prior to the passage of *Dodd Frank Act* in the US, credit rating decisions were perceived as mere “opinions” and therefore subject to influence by the graded firm or by the rating agency’s behavioral biases. After the regulatory reform, credit rating agencies were required to publicize their rating methodologies and their grade decisions have become subject to legal liability. This has reinforced the need for transparency of the rating methodologies and is expected to have made the grading process more rational and comprehensive.

The aim of this paper is to assess the effects of the increased regulation in the credit ratings market on (i) the ability of CRAs to free themselves from behavioral bias and (ii) their capacity to take better account of the cash flow availability and cash generation capacity of debt-issuing firms, as opposed to the accrual-based accounting earnings of these firms potentially subject to opportunistic manipulations.

Two main results arise from our empirical tests. First, there is a systematic and statistically significant negative impact of prior year rating volatility on the current year propensity of a debt issuer to obtain rating upgrade from speculative to investment quality grades. This result shows that credit ratings are persistently impacted by the CRAs perceived volatility of the issuing firm's creditworthiness. Such a finding supports our prediction that rating agencies' judgmental heuristics are driven by loss aversion in the rating adjustment process, subsequent to the initial rational 'anchoring' in financial fundamentals. This loss aversion is observed consistently in all the results and is only marginally impacted by the passage of the *Dodd Frank Act*. That is, the CRAs' loss aversion bias persists even after the passage of the legislation, the purpose of which was to make the rating process more rational and more transparent.

Our results are contradictory with Dimitrov et al. (2015), who find that after the passage of the *Dodd Frank Act*, US CRAs have become more concerned with potential reputational losses due to incorrect rating decisions. Our results show that rating decisions after the reform are still prone to behavioral bias (loss aversion), although to a lower extent as compared to the period before the reform.

Furthermore, our findings corroborate the hypothesis that rating decisions tend to react strongly to cash flow information (Gredil et al., 2022), although this reaction has not become stronger in the period after the passage of *Dodd Frank Act*, and is virtually similar to the reaction to changes in earnings.

We make two incremental contributions relative to the existing literature. First, we model rating methodologies based on the behavioral economics literature. We argue that anchoring and adjustment heuristic process is based initially on a rational 'anchor' composed on potentially relevant economic and financial fundamentals of the debt issuer. Subsequently the 'adjustment' heuristic is prone to behavioral biases such as conservatism and loss aversion.

Second, this paper provides new evidence as to the sensitivity of credit rating agency behavior towards the credit rating grade quality of their clients in the light of the new US legislation. Our analysis takes account of the increasing regulatory interference in credit rating services over time that were intended to address the criticism on rating agencies behavioral biases. We segregate our analysis between the unregulated period 2002-2009 and the subsequent implementation of *Dodd-Frank Act* reforms in 2010.

Third, we find that credit rating grade quality was (not) significantly associated with earnings and cash flow quality in the period prior to (following) the passage of the *Dodd-Frank Act*. This finding questions the expected positive impact of the regulatory reform on the use of cash flows in the rating agency's methodology.

Our findings are robust to alternative specifications of the independent variable (e.g. investment grade, threshold, speculative grade), and to internal validity threats related to endogeneity and external validity threats related to alternative measures of rating quality (i.e., Moody's credit ratings).

Our results are subject to several caveats. First, contrary to the prior literature, we employ a panel of firms that were in continuous existence during the study period 2002-2017. Therefore, our analysis is subject to survivorship bias. We are currently undertaking further robustness checks to examine this issue. Second, our study examines only a relatively small sample of relatively large non-financial S&P 500 rated firms. Consequently, it is possible that our results will not be applicable to rating agency methodology with regard to other types of issuers, such as structured finance vehicles, financial sector, and SME firms. Third, our (ordered) probit structure model incorporates several restrictive econometric assumptions. Therefore, alternative econometric specifications could produce different results.

Subject to these caveats, our major findings provide new evidence on the ameliorating impact of the *Dodd-Frank Act* and subsequent Department of Justice litigation of the provision on the sentiment of S&P towards the credit rating quality of US firms. Our results also support the criticisms of the legal literature that the user pays model potentially causes conflict of interest for credit rating agencies. Finally, further research is needed to substantiate and collaborate our findings in other institutional and industry settings.

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Table 1

Timeline of Key Events – S&P credit ratings methodology

Year	Summary	Impact on methodology
2002	Sarbanes Oxley Act	SEC report investigating the rating agencies' role in securities markets and conflicts of interest (Section 702)
2004	IOSCO Credit rating agency code (revised 2008, 2015)	Principles containing high level objectives that credit rating encouraged to follow concerning their own codes of conduct – "comply or explain" basis
2006	Credit Rating Agency Reform Act	1. Credit rating agencies required to provide a general description of procedures and methodologies in applying to become an NRSROs 2. NRSROs required to provide SEC with audited financial statement on an annual basis (Rule 17g-3) 3. NRSRCO prohibited from issuing or maintaining a credit rating solicited by an entity that provide the NRSRO with net revenue of at least 10% of the total net revenue of the NRSRO (Rule 17g-5(c)(1)) 4. NRSROs disclose and manage conflicts of interest (including issuer-pays model) arising in the normal course of issuing credit rating (Rule 17g-5)
2008	SEC removes references to credit ratings in 38 of its 44 rules and forms	Investors required to undertake independent analysis when buying corporate debt instead of relying on credit ratings
2010	Dodd-Frank Wall Street Reform and Protection Act	1. Creates Office of Credit Ratings to conduct yearly reviews of NRSROs methodologies. 2. SEC required to conduct two-year study to determine 3. Credit rating analysts required to pass qualifying exam and meet CPE requirements 4. Agencies made legally liable for assigning poor quality credit ratings
2014	SEC adopts credit rating agency reform rules	NRSROs must establish, monitor and enforce internal controls on every aspect of their business
2015	Department of Justice lawsuit settlement with S&P	S&P pledges to: 1. "strengthen independence from issuer influence" 2. Improve credit ratings methodology 3. Enhance regulatory compliance and analytical quality

Table 2

Credit ratings of sample firms by year and grade

Panel A: Investment grade sub-sample

year	BBB-	BBB	BBB+	A-	A	A+	AA-	AA	AA+	AAA	Total
2002	47	75	42	33	42	29	9	7	0	7	291
2003	52	65	49	33	43	24	8	6	0	7	287
2004	45	72	47	36	42	21	7	7	0	6	283
2005	48	68	51	35	39	23	7	7	0	6	284
2006	58	66	51	34	37	21	8	6	0	6	287
2007	58	59	58	30	43	17	7	6	0	6	284
2008	57	63	54	29	39	16	10	5	0	5	278
2009	58	72	48	26	39	15	10	5	1	3	277
2010	64	68	50	30	36	17	8	5	1	3	282
2011	58	66	56	30	35	20	5	5	1	3	279
2012	56	77	51	34	34	19	6	4	1	3	285
2013	51	79	47	40	36	18	8	4	1	3	287
2014	45	74	58	39	35	17	7	6	1	2	284
2015	44	84	46	44	28	18	9	4	0	2	279
2016	41	85	46	40	28	17	7	5	0	2	271
2017	43	82	51	32	27	17	6	6	0	2	266
Total	825	1155	805	545	583	309	122	88	6	66	4504

Panel B: Speculative grade sub-sample

year	C	B-	B	B+	BB-	BB	BB+	Total
2002	2	4	10	18	35	42	28	139
2003	1	5	10	13	38	41	35	143
2004	1	2	10	14	37	45	38	147
2005	1	3	8	15	38	49	32	146
2006	0	5	9	17	33	51	28	143
2007	0	4	13	19	32	39	39	146
2008	2	10	12	24	34	35	35	152
2009	7	12	16	21	33	34	30	153
2010	3	6	13	30	32	36	28	148
2011	1	9	11	24	30	40	36	151
2012	1	8	11	24	32	38	31	145
2013	2	6	10	22	28	40	35	143
2014	2	5	10	20	23	44	42	146
2015	4	7	10	22	23	35	47	148
2016	3	7	11	25	29	28	44	147
2017	4	7	12	21	28	25	48	145
Total	34	100	176	329	505	622	576	2342

Table 3

Descriptive Statistics

Panel A: Entire sample period					
Variables	N	Mean	S.D.	Min	Max
SDCR	6,846	0.427	0.557	0.000	5.857
MTB	6,846	1.611	0.695	0.687	4.446
TANG	6,846	0.354	0.252	0.009	0.886
RD	6,846	0.014	0.031	0.000	0.177
RDIND	6,846	0.496	0.500	0.000	1.000
SGA	6,846	0.170	0.119	0.000	0.546
SIZE	6,846	8.477	1.398	5.085	11.85
PROFIT	6,846	0.101	0.067	-0.107	0.323
OPRISK	6,846	0.032	0.031	0.002	0.168
CFO	6,846	0.103	0.061	-0.063	0.296
OPCFO	6,846	0.034	0.025	0.001	0.129
CHETA	6,846	0.081	0.081	0.001	0.390

Panel B: Period before Dodd-Frank Act					
Variables	N	Mean	S.D.	Min	Max
SDCR	3,440	0.431	0.588	0.000	5.857
MTB	3,440	1.581	0.690	0.687	4.446
TANG	3,440	0.357	0.240	0.009	0.886
RD	3,440	0.014	0.032	0.000	0.178
RDIND	3,440	0.484	0.500	0.000	1.000
SGA	3,440	0.171	0.119	0.000	0.546
SIZE	3,440	8.305	1.418	5.085	11.845
PROFIT	3,440	0.105	0.072	-0.107	0.323
OPRISK	3,440	0.034	0.033	0.002	0.168
CFO	3,440	0.108	0.065	-0.063	0.296
OPCFO	3,440	0.038	0.027	0.001	0.129
CHETA	3,440	0.076	0.078	0.001	0.390

Panel C: Period after Dodd-Frank Act					
Variables	N	Mean	S.D.	Min	Max
SDCR	3,406	0.424	0.525	0.000	4.123
MTB	3,406	1.642	0.699	0.687	4.446
TANG	3,406	0.351	0.263	0.009	0.886
RD	3,406	0.014	0.031	0.000	0.178
RDIND	3,406	0.509	0.500	0.000	1.000
SGA	3,406	0.168	0.118	0.000	0.546
SIZE	3,406	8.650	1.356	5.085	11.845
PROFIT	3,406	0.096	0.063	-0.107	0.323
OPRISK	3,406	0.031	0.030	0.002	0.168
CFO	3,406	0.099	0.056	-0.063	0.296
OPCFO	3,406	0.032	0.023	0.002	0.129
CHETA	3,406	0.084	0.081	0.001	0.390

Table 4

Earnings Model of Credit Rating Determinants

	Entire sample period		Period before Dodd-Frank Act		Period after Dodd-Frank Act	
Variables	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects
SDCR	-0.658***	-0.062***	-1.306***	-0.085***	-0.758***	-0.053***
	(0.109)	(0.011)	(0.182)	(0.012)	(0.254)	(0.019)
MTB	0.514***	0.048***	0.204	0.013	0.983***	0.068***
	(0.144)	(0.014)	(0.199)	(0.013)	(0.345)	(0.024)
TANG	2.368**	0.224**	4.985***	0.327***	2.587*	0.180
	(0.988)	(0.093)	(1.173)	(0.072)	(1.566)	(0.110)
RDIND	-0.357	-0.034	-1.142**	-0.074**	-0.304	-0.021
	(0.368)	(0.035)	(0.557)	(0.035)	(0.611)	(0.042)
SGA	3.003**	0.285**	9.041***	0.593***	6.343**	0.441***
	(1.503)	(0.142)	(2.571)	(0.153)	(2.531)	(0.167)
SIZE	0.839***	0.080***	1.850***	0.121***	1.686***	0.117***
	(0.180)	(0.018)	(0.243)	(0.014)	(0.268)	(0.015)
PROFIT	3.552***	0.337***	2.466	0.162	3.457	0.240
	(1.126)	(0.107)	(1.786)	(0.116)	(2.369)	(0.164)
OPRISK	-1.142	-0.108	-4.703	-0.308	-1.242	-0.086
	(2.525)	(0.240)	(4.822)	(0.320)	(4.567)	(0.320)
Constant	-7.428***		-16.63***		-15.79***	
	(1.850)		(2.454)		(2.617)	
Industry controls	Yes		Yes		Yes	
Observations	6,846		3,440		3,406	
Number of id	430		430		430	
Log-Likelihood:	-1381		-639.1		-662.3	
Chi-squared	111.2		138.3		82.17	
Prob Wald:	0.000		0.000		0.000	

Random effect probit estimation using *RATE* as dependent variable. Marginal effects are reported with respect to Investment rate. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5

Cash Flow Model of Credit Rating Determinants

	Entire sample period		Period before Dodd-Frank Act		Period after Dodd-Frank Act	
Variables	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects
SDCR	-0.668***	-0.063***	-1.328***	-0.085***	-0.788***	-0.053***
	(0.110)	(0.011)	(0.188)	(0.013)	(0.268)	(0.019)
MTB	0.552***	0.052***	0.196	0.013	1.018***	0.068***
	(0.140)	(0.013)	(0.227)	(0.014)	(0.335)	(0.022)
TANG	2.104**	0.198**	4.827***	0.310***	2.818	0.188
	(1.031)	(0.096)	(1.170)	(0.071)	(1.759)	(0.117)
RDIND	-0.320	-0.030	-1.155**	-0.074**	-0.360	-0.024
	(0.352)	(0.033)	(0.561)	(0.035)	(0.643)	(0.042)
SGA	2.329	0.219	8.610***	0.553***	5.445**	0.363**
	(1.498)	(0.141)	(2.472)	(0.146)	(2.504)	(0.157)
SIZE	0.867***	0.081***	1.889***	0.121***	1.782***	0.119***
	(0.174)	(0.017)	(0.252)	(0.014)	(0.289)	(0.015)
OPCFO	-2.513	-0.236	-5.637	-0.362	-3.602	-0.240
	(2.969)	(0.281)	(5.212)	(0.334)	(5.656)	(0.383)
CFO	4.093***	0.385***	4.606***	0.296***	3.482*	0.232*
	(1.170)	(0.112)	(1.476)	(0.098)	(2.056)	(0.135)
CHETA	0.975	0.092	0.382	0.025	4.896**	0.326***
	(1.072)	(0.101)	(1.673)	(0.107)	(1.902)	(0.122)
Constant	-7.593***		-16.96***		-16.77***	
	(1.807)		(2.508)		(2.888)	
Industry controls	Yes		Yes		Yes	
Observations	6,846		3,440		3,406	
Number of id	430		430		430	
Log-Likelihood:	-1377		-636.5		-655.2	
Chi-squared	122.8		157.1		78.36	
Prob Wald:	0.000		0.000		0.000	

Random effect probit estimation using *RATE* as dependent variable. Marginal effects are reported with respect to Investment rate. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6

Determinants of credit rating scores according to the Earnings Model distinguishing Threshold-ranked firms

Variables	Entire sample period				Period before Dodd-Frank Act				Period after Dodd-Frank Act			
	Regression	Marginal effects			Regression	Marginal effects			Regression	Marginal effects		
	coefficients	Speculative	Threshold	Invest.	coefficients	Speculative	Threshold	Invest.	coefficients	Speculative	Threshold	Invest.
SDCR	-0.303***	0.076***	-0.014***	-0.062***	-0.278***	0.070***	-0.010***	-0.059***	-0.354***	0.087***	-0.019***	-0.067***
	(0.047)	(0.012)	(0.003)	(0.010)	(0.072)	(0.018)	(0.0036)	(0.016)	(0.092)	(0.022)	(0.005)	(0.017)
MTB	0.146***	-0.039***	0.007***	0.030***	0.201***	-0.0507***	0.0075**	0.043***	0.163*	-0.0400*	0.008*	0.031*
	(0.044)	(0.011)	(0.002)	(0.009)	(0.076)	(0.019)	(0.0034)	(0.016)	(0.090)	(0.022)	(0.005)	(0.017)
TANG	1.045***	-0.263***	0.048**	0.215***	1.620**	-0.409**	0.0610**	0.348**	0.727	-0.179	0.039	0.139
	(0.364)	(0.091)	(0.019)	(0.074)	(0.651)	(0.164)	(0.027)	(0.143)	(0.780)	(0.190)	(0.043)	(0.148)
RDIND	-0.144	0.0361	-0.007	-0.029	-0.149	0.037	-0.005	-0.031	-0.122	0.030	-0.006	-0.023
	(0.122)	(0.031)	(0.006)	(0.025)	(0.137)	(0.034)	(0.005)	(0.029)	(0.131)	(0.032)	(0.007)	(0.025)
SGA	0.730	-0.184	0.033	0.150	3.065**	-0.774**	0.115*	0.658**	-2.162	0.531	-0.117	-0.415
	(0.468)	(0.118)	(0.023)	(0.096)	(1.401)	(0.353)	(0.061)	(0.301)	(1.582)	(0.390)	(0.087)	(0.306)
SIZE	0.140***	-0.035***	0.006**	0.029***	0.349***	-0.088***	0.013**	0.075***	-0.0101	0.002	-0.001	-0.002
	(0.052)	(0.013)	(0.003)	(0.011)	(0.114)	(0.029)	(0.0052)	(0.025)	(0.141)	(0.034)	(0.007)	(0.027)
PROFIT	1.403***	-0.353***	0.064***	0.289***	1.971***	-0.498***	0.074**	0.423***	-0.477	0.117	-0.025	-0.091
	(0.340)	(0.084)	(0.020)	(0.069)	(0.597)	(0.150)	(0.030)	(0.128)	(0.835)	(0.206)	(0.045)	(0.161)
OPRISK	-0.590	0.149	-0.027	-0.122	-0.071	0.0180	-0.0026	-0.015	-2.672**	0.657**	-0.144*	-0.513**
	(0.687)	(0.172)	(0.032)	(0.141)	(1.402)	(0.354)	(0.052)	(0.301)	(1.344)	(0.331)	(0.078)	(0.258)
Industry controls	Yes				Yes				Yes			
Panel data indicators	Yes				Yes				Yes			
Observations	6,846				3,440				3,406			
Pseudo-R	0.278				0.269				0.301			
Log-Likelihood	-5,340				-2,727				-2,557			
Chi-squared	348.5				310.5				294.1			
Prob Wald	0.000				0.000				0			

Ordered probit estimation using *RATE'* as dependent variable. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7

Determinants of credit rating scores according to the Cash Flow Model considering Threshold-ranked firms

Variables	Entire sample period				Period before Dodd-Frank Act				Period after Dodd-Frank Act			
	Regression	Marginal effects			Regression	Marginal effects			Regression	Marginal effects		
	coefficients	Speculative	Threshold	Invest.	coefficients	Speculative	Threshold	Invest.	coefficients	Speculative	Threshold	Invest.
SDCR	-0.303***	0.077***	-0.014***	-0.062***	-0.275***	0.071***	-0.011***	-0.059***	-0.356***	0.087***	-0.019***	-0.068***
	(0.046)	(0.011)	(0.003)	(0.010)	(0.072)	(0.018)	(0.003)	(0.016)	(0.092)	(0.022)	(0.005)	(0.017)
MTB	0.174***	-0.044***	0.008***	0.036***	0.237***	-0.0608***	0.009**	0.051***	0.130	-0.032	0.007	0.025
	(0.042)	(0.011)	(0.003)	(0.009)	(0.075)	(0.019)	(0.004)	(0.016)	(0.095)	(0.023)	(0.005)	(0.018)
TANG	0.875**	-0.221**	0.041**	0.180**	1.301**	-0.334**	0.052**	0.282**	0.874	-0.214	0.046	0.167
	(0.380)	(0.096)	(0.020)	(0.078)	(0.626)	(0.160)	(0.026)	(0.138)	(0.782)	(0.190)	(0.043)	(0.148)
RDIND	-0.173	0.0435	-0.008	-0.035	-0.186	0.047	-0.0076	-0.040	-0.151	0.037	-0.0081	-0.029
	(0.122)	(0.031)	(0.006)	(0.025)	(0.137)	(0.034)	(0.006)	(0.029)	(0.133)	(0.032)	(0.007)	(0.025)
SGA	0.454	-0.115	0.021	0.093	1.939	-0.498	0.078	0.420	-1.176	0.287	-0.062	-0.224
	(0.482)	(0.122)	(0.023)	(0.099)	(1.272)	(0.326)	(0.056)	(0.274)	(1.484)	(0.362)	(0.080)	(0.283)
SIZE	0.140***	-0.035***	0.007**	0.029***	0.350***	-0.089***	0.014***	0.075***	0.025	-0.006	0.001	0.0048
	(0.053)	(0.014)	(0.003)	(0.011)	(0.108)	(0.028)	(0.005)	(0.024)	(0.143)	(0.035)	(0.007)	(0.027)
OPCFO	-0.707	0.179	-0.033	-0.145	-0.231	0.0594	-0.009	-0.050	-3.133**	0.765**	-0.167*	-0.598**
	(0.786)	(0.198)	(0.037)	(0.162)	(1.428)	(0.367)	(0.057)	(0.310)	(1.596)	(0.388)	(0.092)	(0.301)
CFO	1.493***	-0.377***	0.070***	0.307***	1.362**	-0.350**	0.0551**	0.295**	0.901	-0.220	0.048	0.172
	(0.346)	(0.086)	(0.021)	(0.071)	(0.574)	(0.146)	(0.027)	(0.122)	(0.798)	(0.195)	(0.043)	(0.153)
CHETA	-0.151	0.0382	-0.007	-0.031	-0.356	0.0915	-0.014	-0.077	0.540	-0.132	0.029	0.103
	(0.323)	(0.082)	(0.015)	(0.067)	(0.628)	(0.161)	(0.025)	(0.136)	(0.743)	(0.182)	(0.040)	(0.142)
Industry indicators	Yes				Yes				Yes			
Panel data indicators	Yes				Yes				Yes			
Observations	6,846				3,440				3,406			
Pseudo-R	0.277				0.261				0.305			
Log-Likelihood	-5,346				-2,759				-2542			
Chi-squared	349.8				302.8				293.5			
Prob Wald	0.000				0.000				0.000			

Ordered probit estimation using *RATE'* as dependent variable. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8

Earnings Model of Credit Rating Determinants – robustness test with Moody's rates

	Entire sample period		Period before Dodd-Frank Act		Period after Dodd-Frank Act	
Variables	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects
SDCR	-0.699***	-0.077***	-1.044***	-0.090***	-0.752**	-0.052**
	(0.128)	(0.014)	(0.207)	(0.018)	(0.300)	(0.020)
MTB	0.372**	0.041**	0.174	0.015	1.137***	0.078***
	(0.169)	(0.019)	(0.221)	(0.019)	(0.360)	(0.024)
TANG	1.905**	0.208**	2.789***	0.241***	2.960*	0.203*
	(0.899)	(0.097)	(1.082)	(0.087)	(1.633)	(0.109)
RDIND	0.360	0.040	0.022	0.002	0.239	0.016
	(0.249)	(0.027)	(0.501)	(0.043)	(0.553)	(0.038)
SGA	3.490**	0.382**	6.366***	0.550***	9.181***	0.629***
	(1.387)	(0.149)	(2.074)	(0.169)	(2.817)	(0.173)
SIZE	0.994***	0.109***	1.526***	0.132***	1.961***	0.134***
	(0.195)	(0.019)	(0.250)	(0.016)	(0.384)	(0.017)
PROFIT	3.488***	0.382***	2.006	0.173	4.669*	0.320*
	(1.150)	(0.129)	(1.629)	(0.143)	(2.562)	(0.176)
OPRISK	-0.504	-0.055	-3.190	-0.276	-0.754	-0.052
	(2.133)	(0.233)	(3.855)	(0.330)	(4.189)	(0.287)
Constant	-9.123***		-13.11***		-19.82***	
	(1.875)		(2.328)		(3.722)	
Industry controls	Yes		Yes		Yes	
Observations	5,683	5,683	2,853	2,853	2,830	2,830
Number of id	357		357		357	
Log-Likelihood:	-1274		-629.5		-537.8	
Chi-squared	105.9		84.89		62.58	
Prob Wald:	0.000		0.000		7.60e-09	

Random effect probit estimation using *RATE"* as dependent variable. Marginal effects are reported with respect to Investment rate. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9

Cash Flow Model of Credit Rating Determinants – robustness test with Moody's rates

	Entire sample period		Period before Dodd-Frank Act		Period after Dodd-Frank Act	
Variables	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects
SDCR	-0.688***	-0.075***	-1.049***	-0.090***	-0.719**	-0.049**
	(0.126)	(0.014)	(0.209)	(0.018)	(0.297)	(0.020)
MTB	0.465***	0.051***	0.198	0.0170	1.179***	0.081***
	(0.154)	(0.017)	(0.221)	(0.019)	(0.329)	(0.021)
TANG	1.463	0.160	2.444**	0.210**	2.553	0.175*
	(0.933)	(0.100)	(1.116)	(0.090)	(1.586)	(0.105)
RDIND	0.325	0.036	0.001	0.0001	0.227	0.016
	(0.261)	(0.029)	(0.498)	(0.0427)	(0.534)	(0.037)
SGA	2.941**	0.321**	6.069***	0.520***	9.191***	0.631***
	(1.362)	(0.146)	(2.067)	(0.167)	(2.816)	(0.169)
SIZE	1.012***	0.110***	1.544***	0.132***	1.900***	0.130***
	(0.193)	(0.019)	(0.245)	(0.016)	(0.372)	(0.017)
OPCFO	-0.905	-0.099	-5.695	-0.488	-6.965	-0.478
	(2.725)	(0.297)	(4.285)	(0.360)	(5.450)	(0.381)
CFO	3.310***	0.361***	2.748*	0.236*	6.256***	0.430**
	(1.129)	(0.126)	(1.438)	(0.127)	(2.380)	(0.167)
CHETA	-0.719	-0.078	-0.202	-0.017	-0.761	-0.052
	(1.112)	(0.121)	(1.559)	(0.134)	(2.388)	(0.163)
Constant	-9.063***		-13.04***		-19.13***	
	(1.873)		(2.334)		(3.641)	
Industry controls	Yes		Yes		Yes	
Observations	5,683	5,683	2,853	2,853	2,830	2,830
Number of id	357		357		357	
Log-Likelihood:	-1275		-628.3		-534.1	
Chi-squared	102.7		90.60		71.03	
Prob Wald:	0.000		0.000		5.19e-10	

Random effects probit estimation using *RATE"* as dependent variable. Marginal effects are reported with respect to Investment rate. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10

Earnings Model of Credit Rating Determinants – Endogeneity-corrected Test

	Entire sample period		Period before Dodd-Frank Act		Period after Dodd-Frank Act	
Variables	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects
L.SDCR	-0.568***	-0.052***	-1.092***	-0.069***	-0.572***	-0.040***
	(0.099)	(0.010)	(0.187)	(0.012)	(0.183)	(0.014)
L.MTB	0.641***	0.059***	0.709***	0.045***	0.766**	0.053**
	(0.158)	(0.015)	(0.251)	(0.015)	(0.320)	(0.022)
L.TANG	2.322***	0.214***	5.249***	0.330***	2.655**	0.183**
	(0.850)	(0.0781)	(1.319)	(0.0756)	(1.221)	(0.086)
L.RDIND	-0.199	-0.018	-0.803	-0.050	0.149	0.010
	(0.373)	(0.035)	(0.545)	(0.034)	(0.449)	(0.031)
L.SGA	2.520*	0.233*	10.02***	0.629***	5.708***	0.394***
	(1.363)	(0.125)	(2.969)	(0.162)	(2.040)	(0.132)
L.SIZE	0.884***	0.082***	1.881***	0.118***	1.626***	0.112***
	(0.189)	(0.0178)	(0.264)	(0.013)	(0.266)	(0.015)
L.PROFIT	4.543***	0.420***	4.117*	0.259*	6.083**	0.420**
	(1.467)	(0.135)	(2.236)	(0.138)	(2.663)	(0.180)
L.OPRISK	-3.985	-0.368	-11.21	-0.704	0.798	0.055
	(2.995)	(0.279)	(6.989)	(0.439)	(4.943)	(0.340)
Constant	-8.112***		-18.38***		-15.36***	
	(1.915)		(2.717)		(2.583)	
Industry controls	Yes		Yes		Yes	
Observations	6,416	6,416	3,010	3,010	3,406	3,406
Number of id	430		430		430	
Log-Likelihood:	-1277		-574.3		-669.5	
Chi-squared	135.3		91.62		74.62	
Prob Wald:	0.000		0.000		0.000	

Random effect probit estimation using *RATE* as dependent variable. One-year lagged values are used for all independent variables (prefix 'L.'). Marginal effects are reported with respect to Investment rate. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11

Cash Flow Model of Credit Rating Determinants - Endogeneity-corrected Test

	Entire sample period		Period before Dodd-Frank Act		Period after Dodd-Frank Act	
Variables	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects	Regression coefficients	Marginal effects
L.SDCR	-0.578***	-0.053***	-1.182***	-0.069***	-0.601***	-0.041***
	(0.102)	(0.010)	(0.190)	(0.012)	(0.205)	(0.015)
L.MTB	0.694***	0.063***	0.744***	0.044***	0.786**	0.053***
	(0.143)	(0.013)	(0.253)	(0.014)	(0.305)	(0.020)
L.TANG	1.919**	0.175**	5.582***	0.328***	2.456**	0.166**
	(0.891)	(0.080)	(1.390)	(0.074)	(1.239)	(0.084)
L.RDIND	-0.133	-0.012	-0.783	-0.046	0.099	0.007
	(0.361)	(0.033)	(0.553)	(0.0322)	(0.493)	(0.033)
L.SGA	1.500	0.137	10.22***	0.600***	4.265**	0.288**
	(1.385)	(0.126)	(3.141)	(0.158)	(1.977)	(0.128)
L.SIZE	0.893***	0.081***	1.982***	0.116***	1.646***	0.111***
	(0.185)	(0.017)	(0.282)	(0.013)	(0.270)	(0.015)
L.OPCFO	-7.414**	-0.675**	-12.060**	-0.708**	-12.530*	-0.845*
	(3.122)	(0.285)	(5.849)	(0.330)	(6.612)	(0.459)
L.CFO	5.065***	0.461***	6.275***	0.368***	7.494***	0.505***
	(1.284)	(0.118)	(2.014)	(0.117)	(2.191)	(0.141)
L.CHETA	1.386	0.126	3.128	0.184	4.020**	0.271**
	(1.106)	(0.101)	(2.031)	(0.116)	(1.889)	(0.126)
Constant	-8.022***		-19.72***		-15.31***	
	(1.862)		(2.925)		(2.637)	
Industry controls	Yes		Yes		Yes	
Observations	6,416	6,416	3,010	3,010	3,406	3,406
Number of id	430		430		430	
Log-Likelihood:	-1271		-570.5		-655.2	
Chi-squared	140.1		100.7		86.17	
Prob Wald:	0.000		0.000		0.000	

Random effect probit estimation using *RATE* as dependent variable. One-year lagged values are used for all independent variables (prefix 'L.'). Marginal effects are reported with respect to Investment rate. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 1

Number of sample firms by S&P credit rating grade 2002-2017

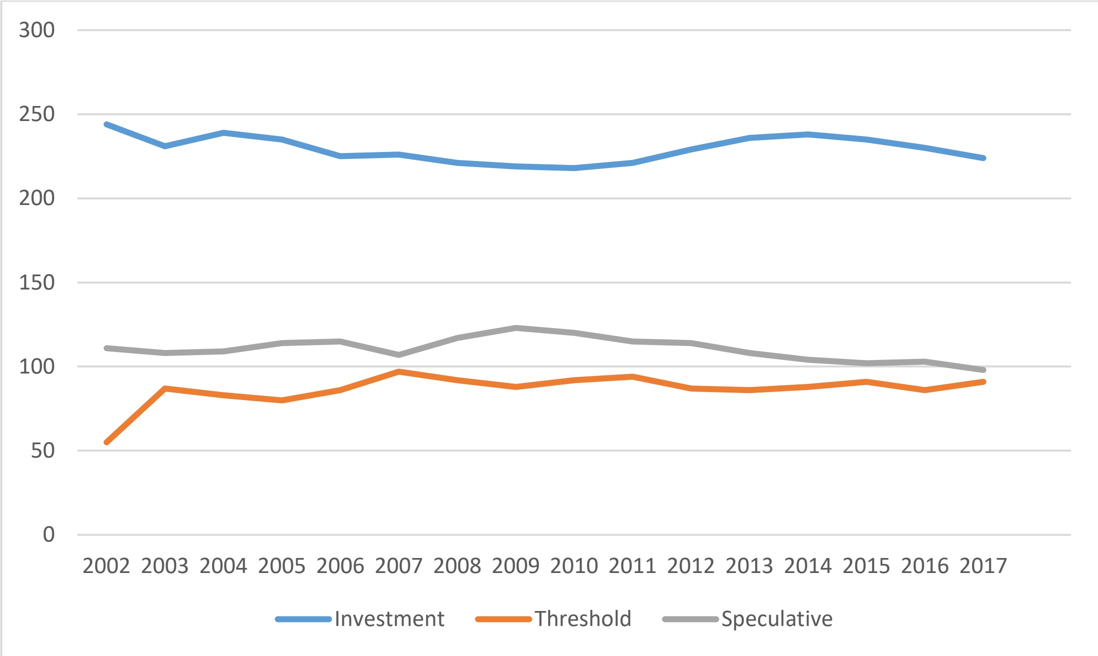


Figure 2

Standard deviation of return by Credit rating grade quality

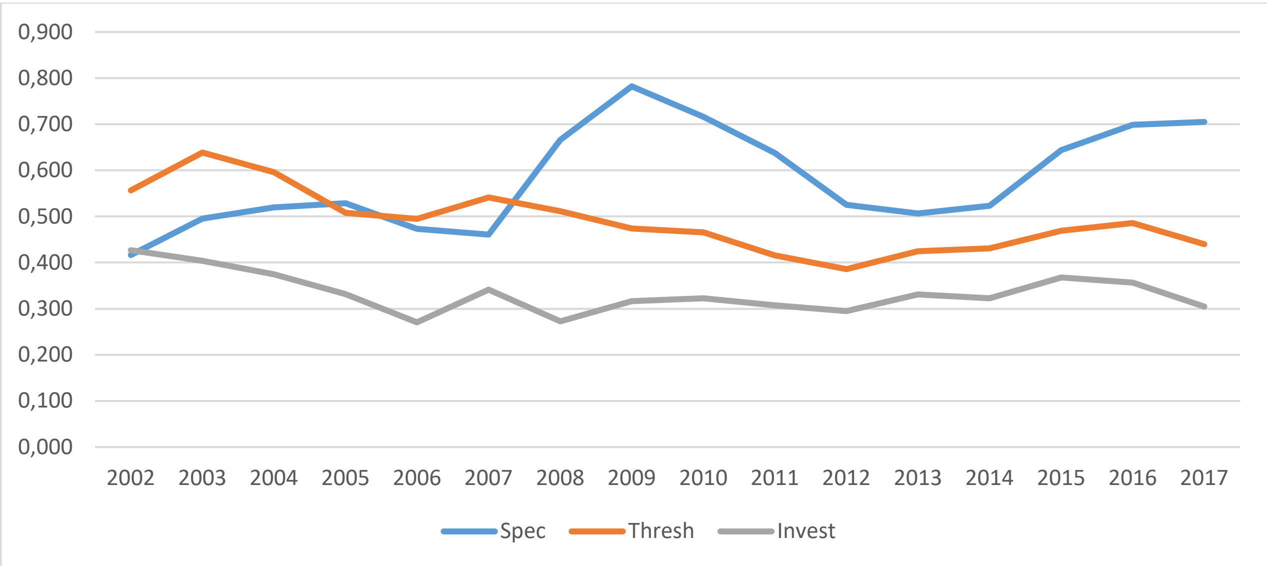
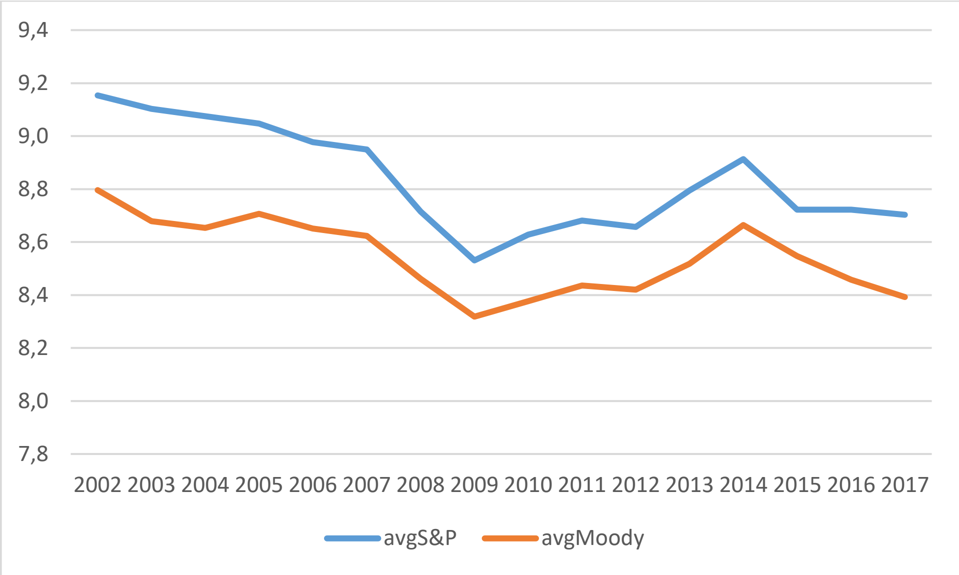


Figure 3

Credit rating grades Moody's v S&P 2002-2017

Panel A: Average credit rating grade



Panel B: Standard deviation of credit rating grade