Market reactions to credit rating changes:

The impact of using value-based performance measures

Abstract

Value-based (VB) management is an approach that seeks to align the interests of managers and shareholders by encouraging actions that maximize shareholder value. One possible approach to increase shareholder value is to optimize risk taking and the cost of capital. This paper focuses on rating changes that reflect credit risk. We use option pricing theory to analyze the effect of increased credit risk—as reflected by negative rating changes—on shareholder value. Increased credit risk can be the result of a higher cash flow variance, which affects the cost of debt, the cost of equity and shareholder value. By comparing capital market reactions to rating changes for users and non-users of VB performance measures, we investigate the shareholder value effect of using such measures. With a sample of 115 rating changes of listed German firms between 1996 and 2014, we separately analyze market reactions to downgrades and upgrades. We find that using VB performance metrics is positively associated with market reactions to downgrade announcements and thus with shareholder value. This indicates that VB measures lead to a risk-taking strategy that is in line with shareholders' interests, and such measures reduce information asymmetries. Further, using VB metrics is not significantly associated with market reactions to upgrade announcements. This might be the result of lower information asymmetries in the context of upgrades.

Keywords: value-based management, issuer rating, downgrades, upgrades, event study

JEL: M41, G14, G32

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1 Introduction

We investigate whether the shareholder value effect of changes in firm risk reflected in credit rating changes differs for users and non-users of value-based (VB) performance metrics. VB management (VBM) systems are integrated management frameworks that direct corporate actions toward the aim of maximizing shareholder value (RAPPAPORT, 1998; SCHEIPERS ET AL., 2003). VB performance metrics operationalize the objective of creating shareholder value and are therefore a central component of these systems (STEWART, 1995). According to the VBM approach, shareholder value is increased if and only if the generated return exceeds the cost of capital (FRUHAN, 1979). Thus, management has three levers to influence value creation: the invested capital, the return on invested capital, and the cost of capital, which represents the expected risk-adjusted return requirements of equity and debt investors (STEWART, 1991).

A key question for practitioners and researchers alike concerns the effect of the use of VB performance metrics on shareholder value. Although this research question has received much attention, evidence regarding the influence of VB performance metrics on performance remains inconclusive (ITTNER AND LARCKER, 2001; LUEG AND SCHÄFFER, 2010; RAPP ET AL., 2011). The implementation of a VBM system takes months or even years, and thus the exact adoption date is often unknown or ambiguous. Hence, measuring the effect of the adoption of these systems is difficult. Further, empirical evidence regarding the effect of using VB performance metrics on the cost of capital and its underlying factors is scarce. RYAN AND TRAHAN (2007) show that the cost of capital steadily decreases after the implementation of a VBM system. SCHULTZE ET AL. (2017) study the effects of VBM and VB reporting on information asymmetries and the cost of capital. However, the cost of capital is not only associated with information asymmetries but also with firm risk (FAMA AND FRENCH, 2004; HAIL AND LEUZ, 2006), which may also be affected by VBM.

In our investigation, we focus on the effect of VBM on firm risk and its evaluation by shareholders. We analyze external credit ratings because they are used to assess issuers' risk and are associated with shareholder and debt value (KLIGER AND SARIG, 2000). More precisely, external credit ratings provide evaluations of credit risk, which MOODY'S INVESTORS SERVICE (2017, p. 40) defines as "the risk that an entity may not meet its contractual, financial obligations as they come due and any estimated financial loss in the event of default".[1] External ratings contain publicly available information but also provide new information about a firm's future financial prospects and the inherent risk to the market and thus fulfill an information function[2] (EDERINGTON ET AL., 1987; HOLTHAUSEN AND LEFTWICH, 1986; KLIGER AND SARIG, 2000). Lower ratings signal higher default risk[3]. Thus, downgrades result in higher capital costs for debt (FRIDSON AND GARMAN, 1998; HEINKE, 1998) and ceteris paribus a decrease in shareholder value. However, ratings are associated not only with a firm's cost of debt but also with the cost of equity and shareholder value. Ratings are frequently the result of changes in financial leverage and/or future cash flow volatility (GOH AND EDERINGTON, 1993; HOLTHAUSEN AND LEFTWICH, 1986). If downgrades are the result of high financial or operational risks, they can also be positively associated with shareholder value (HOLTHAUSEN AND LEFTWICH, 1986). In accordance with option pricing theory, shareholders can benefit from higher risk because their liability for losses is limited, whereas their chances of high returns are not (BLACK AND SCHOLES, 1973; MERTON, 1973; MERTON, 1974). Thus, even if firms cannot fully control firm risk, they should try to approach the optimal risk-return relation to maximize shareholder value. In our study, we use rating changes as a signal of changes in a firm's risk and financial prospects, which can be the result of external effects or management decisions. We differentiate rating changes into downgrades and upgrades because information asymmetries are more pronounced for downgrades compared to upgrades (EDERINGTON AND GOH, 1998; KIM AND NABAR, 2007). Because VBM systems seek to align the interests of management and shareholders and reduce information asymmetries, the effect of VBM systems is likely to differ for downgrades and upgrades. We predict that the shareholder value effect associated with downgrades is more positive for firms that use VB performance metrics. For upgrades, we do not expect to find significant differences between VB metric users and non-users due to less asymmetric information. To

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1 In our study, we focus on issuer ratings, which incorporate "all external support that is expected to apply to all current and future issuance of senior unsecured financial obligations and contracts, such as explicit support stemming from a guarantee of all senior unsecured financial obligations and contracts, and/or implicit support for issuers subject to joint default analysis (e.g., banks and government-related issuers). Issuer Ratings do not incorporate support arrangements, such as guarantees, that apply only to specific (but not to all) senior unsecured financial obligations and contracts" (MOODY'S INVESTORS SERVICE, 2017, p. 8).

2 BANNIER AND HIRSCH (2010) argue that by providing watchlists, rating agencies also fulfill a monitoring function. Further, from the issuer's point of view, ratings can serve as admission requirements for international capital markets or to exploit new and cheaper funding alternatives and thus can lower financing costs (SCHNABEL, 1996).

3 Here and in the following, we use default risk as a synonym for credit risk as defined above.

proxy for the shareholder value effect of credit ratings, we apply the event study methodology to investigate whether using VB performance measures is positively associated with shareholders' valuation of the firm. Since the exact announcement dates of rating changes can be obtained from the rating agencies, we are able to conduct a short-window analysis.

We exploit a sample of 115 rating changes (downgrades and upgrades) involving listed German firms that were announced by Moody's between 1996 and 2014. We analyze the association between abnormal returns surrounding the announcements and the use of VB metrics while controlling for certain characteristics of the rating change, the rating subject and the firm's environment. As predicted, we find a significantly positive effect of the use of VB measures on investors' reaction to downgrade announcements. In the case of upgrades, the use of VB metrics is not associated with significant abnormal returns. We also consider the sophistication of the VBM system by determining whether firms use VB measures for their control system and/or for their compensation system. We do not find significant differences with regard to VBM system sophistication for either downgrades or upgrades.

Our study contributes to the literature in at least three ways. First, we add to the literature stream on the performance effects of VBM systems. The prior literature often analyzes whether performance increases after the implementation of VBM systems (e.g., HOGAN AND LEWIS, 2005; RAPP ET AL., 2011; RYAN AND TRAHAN, 2007), and a few studies analyze the performance effects of corporate decisions such as M&As and divestments (e.g., KNAUER ET AL., 2017). Management also makes decisions that affect the volatility of future cash flows and the capital structure and thus firm risk. Because firm risk affects potential future returns and the cost of capital, risk taking and risk management are important levers to increase shareholder value. Management cannot actively influence a firm's rating. However, their decisions are one factor (among others) that affects firm risk. Because firm risk is reflected in external credit ratings, we can use credit ratings as an indicator for the level of firm risk and a firm's financial prospects. Thus, we analyze the capital market reactions to rating changes for VB metric users and non-users. Second, we contribute to the literature on the effect of rating changes. A substantial number of studies analyze the effect of credit rating changes on stock returns. We show that management control systems, such as VBM systems, positively affect capital market reactions to downgrades. Third, the prior VBM research and most studies on rating changes focus on the U.S. market (e.g., GOH AND EDERINGTON, 1999; HAND ET AL., 1992; HOLTHAUSEN AND LEFTWICH, 1986; LOVATA AND COSTIGAN, 2002; RYAN AND TRAHAN, 2007), which is characterized by different corporate governance structures and a higher capital market orientation compared to the German market that we analyze (ANTONIOU ET AL., 2008; GOERGEN ET AL., 2008). Prior research finds that low shareholder orientation is negatively associated with the efficacy of the implementation of VB performance metrics and thus the performance effects of VBM (FIRK ET AL., 2016). Further, capital market orientation might affect the speed and level of capital market reactions to rating announcements. For these reasons, the effect of VB metric use is probably lower in the German market than in the U.S.; thus, a German sample presents an interesting setting.

The remainder of the paper proceeds as follows. Section 2 summarizes the relevant findings from the related literature and presents our hypotheses. Section 3 describes the sample and research design. Section 4 presents our results, and Section 5 concludes.

2 Related literature and hypotheses development

2.1 Related literature

VBM systems are integrated management frameworks that aim to facilitate decision-making and to align management's interests with those of shareholders, thereby reducing agency costs and increasing shareholder value (RAPPAPORT, 1998). VBM systems mitigate agency problems by increasing transparency, facilitating the monitoring of management performance and motivating employees to act in the interests of shareholders (ELGHARBAWY AND ABDEL-KADER, 2013). Key components of VBM systems are VB performance metrics that operationalize the objective of shareholder value maximization (SCHEIPERS ET AL., 2003; STEWART, 1995). These VB metrics are used for strategy development, performance evaluation, management compensation and communications purposes (MALMI AND IKÄHEIMO, 2003; RYAN AND TRAHAN, 2007; SCHEIPERS ET AL., 2003). Thus, they repeatedly remind and motivate managers to increase shareholder value. While the advocated VB metrics vary between different approaches of VBM, all of them take into account the return and the cost of capital. According to the VBM concept, shareholder value is increased if and only if the generated return exceeds the cost of capital (FRUHAN, 1979). Thus, VB metrics can lead to better decisions compared to traditional performance metrics, which do not include the cost of equity. Thus, VBM systems should enable managers to develop and exercise value-creating strategies that lead to the more efficient use of capital, increasing returns on invested capital, and/or a decrease of the cost of capital (RAPPAPORT, 1998).

Although VB metrics theoretically encourage value-increasing actions, LUEG AND SCHÄFFER (2010) state that examining the entirety of empirical studies on the performance effect of VBM leads to an inconclusive picture. This is especially noteworthy since the existing literature attributes remarkable potential to VBM (e.g., SCHEIPERS ET AL., 2003). For example, RYAN AND TRAHAN (2007), RAPP ET AL. (2011), FIRK ET AL. (2016), and KNAUER ET AL. (2017) find a positive effect of VBM on firm performance[4], whereas CORDEIRO AND KENT JR. (2001) and HOGAN AND LEWIS (2005) do not identify a statistically significant influence. Moreover, there is a small pool of studies that even find a negative relation between VBM and firms' stock performance (GRIFFITH, 2004). However, LUEG AND SCHÄFFER (2010) note that only studies that analyze the depth of implementation and value-oriented performance simultaneously provide a meaningful reference for evaluating the effects of VBM. They identify four different studies that fulfill this criterion and consistently support a positive correlation between holistic VBM and firm success (LUEG AND SCHÄFFER, 2010). Nevertheless, it should be noted that the question of a minimum requirement for the existence of a VBM system (e.g., MALMI AND IKÄHEIMO, 2003; WEBER ET AL., 2017) as well as the question regarding the point at which such a system is considered successful leave room for interpretation (LUEG AND SCHÄFFER, 2010).

Given the conceptual arguments about the positive effects of VBM and the results of empirical research, we assume that the use of VB metrics aligns the interests of management and shareholders and is associated with a positive shareholder value effect. The level of the cost of capital is one major lever to influence shareholder value. However, prior research on the effects of VBM on the cost of capital and its underlying factors is scarce. RYAN AND TRAHAN (2007) show that the cost of capital steadily decreases after the implementation of a VBM system. Another noteworthy exception is SCHULTZE ET AL. (2017), who study the effects of VBM and VB reporting on information asymmetries and the cost of capital. However, the cost of capital is affected not only by information asymmetries but also by firm risk (FAMA AND FRENCH, 2004; HAIL AND LEUZ, 2006), which may also be affected by VBM. Thus, we predict that VB metric users will manage firm risk to increase shareholder value. To detect changes in firm risk, we use credit ratings. Rating changes assess credit risk and are associated with shareholder value and debt value (KLIGER AND SARIG, 2000).

External credit ratings reflect a firm's financial prospects and the inherent risk (probability of default and loss rate given default) for debt investors (HEINKE, 2000; BRAUN, 2002; ASHBAUGH-SKAIFE ET AL., 2006). The expected return on debt is based on a risk-free rate plus a premium that takes into

[4] Studies analyzing the performance effects of VBM use either stock-based, accounting-based or self-rating measures of firm performance.

account a firm's default probability (MERTON, 1974). Thus, if ratings provide investors with new information about a firm's default risk, this can ceteris paribus affect the cost of debt and thereby shareholder value. However, increased risk does not necessarily decrease shareholder value despite a higher cost of debt: Option pricing theory argues that shareholders can benefit from downgrades. BLACK AND SCHOLES (1973) and MERTON (1974) argue that debt and equity holders' claims resemble options. Debtholders receive fixed interest and the repayment of their loan; thus, their potential returns are limited. In the event of a firm's default, proceeds are first allocated to debtholders, who are still likely to suffer severe losses. Thus, debtholders' claims can be interpreted as the sum of the payoffs of a riskless bond and a short put. According to the option pricing theory developed by BLACK AND SCHOLES (1973) and MERTON (1974), debtholders' claims decrease like the value of a short put if volatility increases. Shareholders' claims equal a long call because they are entitled to the residual cash flows and thus have a chance to benefit from unlimited upside potential if the cash flow volatility is high. In the event of a firm's default, their claims are subordinate, but their liability for losses is limited to their initial investment. Thus, shareholders' claims increase with the value of a long call if volatility increases (BLACK AND SCHOLES, 1973). Hence, a downgrade due to increased volatility is detrimental to debtholders but increases shareholder value. A wealth redistribution effect from existing bondholders to shareholders can also be shown for an increase in leverage (BLACK AND SCHOLES, 1973). Further, an increased leverage ratio can, under certain circumstances, mitigate agency problems between managers and shareholders and thus may be associated with higher shareholder value (HARRIS AND RAVIV, 1990; HARRIS AND RAVIV, 1991; HIRSHLEIFER AND THAKOR, 1992; STULZ, 1990).

Empirical research on rating changes presents highly consistent insights, even though there are some exceptions according to HEINKE (2000). HEINKE (2000) and HUNDT (2015) provide a detailed presentation of the relevant studies analyzing capital market reactions to rating changes. Overall, the majority of studies find negative abnormal returns following a rating downgrade (e.g., BANNIER AND HIRSCH, 2010; CHUNG ET AL., 2012; EDERINGTON AND GOH, 1998; HOLTHAUSEN AND LEFTWICH, 1986), consistent with deteriorating financial prospects (e.g., due to unexpected economic downturns) and/or an increased cost of debt. GOH AND EDERINGTON (1993) focus on option pricing theory and predict that the capital market reaction to downgrades will be conditioned by the reason published by the rating agencies. They find a negative capital market reaction to announcements of downgrades associated with deteriorating financial prospects and no market reaction if the downgrades are associated with an increase in firms' leverage. They argue that downgrades due to changes in leverage are positively associated with shareholder value but are often the result of past actions and thus are no surprise. Most studies investigating upgrades find a non-significant influence of upgrades on the stock's performance (e.g., BANNIER AND HIRSCH, 2010; DICHEV AND PIOTROSKI, 2001; GRIFFIN AND SANVICENTE, 1982; HOLTHAUSEN AND LEFTWICH, 1986). This asymmetric market reaction to downgrades and upgrades suggests either that rating agencies announce upgrades in less timely manner because the impact of a late rating change is less severe or that firms tend to report 'good news' earlier than 'bad news' to the market (EDERINGTON AND GOH, 1998; HOLTHAUSEN AND LEFTWICH, 1986; KIM AND NABAR, 2007).

To the best of our knowledge, differences in the performance effects of rating changes between VB metric users and non-users have not been the focus of prior research thus far. To close this gap, we subsequently derive hypotheses on a theoretical basis that then serve as the starting point for an event study analysis.

2.2 Hypotheses development

Although the focus of the shareholder value approach is on a firm's investors, whereas the addressees of an external rating assessment are potential outside creditors, both share some common ground. First, it is evident that they both consider future cash flows (GLEIßNER AND FÜSER, 2014). In the context of external ratings, the sufficiency of future cash flows to cover interest and principal payments determines a firm's default risk. A firm's rating is likely to decrease if expectations of future cash flows are revised downward or the variance of its future cash flows increases and thus the likelihood of default (ASHBAUGH-SKAIFE ET AL., 2006). In the context of the shareholder value approach, cash flows and the cost of capital are used to determine the company's value (RAPPAPORT, 1998). Thus, external ratings contain information that substantially influence shareholder value.

We first focus on the effect of credit ratings on the cost of debt. The higher (lower) the assigned rating is, the lower (higher) the expected default risk and hence the cost of debt (EVERLING AND TRIEU, 2007; MERTON, 1974). This leads ceteris paribus to a reduction (increase) in the weighted average cost of capital and to an increase (reduction) in the level of VB performance measures and shareholder value. Following this line of argument, which focuses on the cost of debt only, any VB metric user should consequently strive for the highest possible rating in order to maximize shareholder value. Hence, we would expect a negative (positive) capital market reaction to downgrades (upgrades).

However, rating changes also reflect changes in future cash flows and thus affect the cost of equity and shareholder value. Downgrades caused by deteriorating financial prospects (e.g., due to unexpected economic downturns) point to a potential negative development of expected cash flows and thus of shareholder value. Hence, we would expect a negative capital market reaction. Because shareholders' claims equal a long call, option pricing theory helps to analyze the effect of rating changes on shareholder value. According to option pricing theory, downgrades caused by an increase of leverage (e.g., after a leveraged buy-out or debt-financed expansion) or an (anticipated) increase in the variance of a firm's cash flows are arguably associated with an increase in shareholder value (BLACK AND SCHOLES, 1973; GOH AND EDERINGTON, 1993; HOLTHAUSEN AND LEFTWICH, 1986).

The use of VBM performance measures can impact the shareholder value effect of rating changes. In the following, we discuss the expected absolute shareholder value effect of rating changes for VB metric users and the relative shareholder value effect compared to non-users. First, VBM systems seek to align the interests of management and shareholders by encouraging actions that generate a rate of return that fulfills the market's expectations and accordingly maximizes shareholder value (RAPPAPORT, 1998). Thus, even if firms cannot fully control firm risk, we argue that VB metric users trade off the positive and negative effects of risk taking on the return on capital and cost of capital and thus on shareholder value. In contrast to non-users of VB metrics, they take into consideration the effect of risk on not only the cost of debt but also the cost of equity (FRUHAN, 1979). Thus, if a firm is downgraded for reasons within the control of management, we argue that for VB metric users, this downgrade is presumably the result of management decisions in line with shareholder interests. For this reason, we expect a non-negative capital market reaction to rating changes of VB metric users. Further, we expect this capital market reaction to be more positive for VB metric users compared to non-users.

Second, we argue that investors have greater confidence in VB metric users (RAPP ET AL., 2011; STEWART, 1991). Investors can assume that the management of VBM firms represents their interests at all times, and thus a rating downgrade does not lead to a reallocation of the investors' portfolios, and shareholder value remains unaffected. This also leads to the prediction of a non-negative capital market reaction to rating changes of VB metric users, which we assume to be more positive than for non-users of such measures.

Third, VBM and VB reporting aim to decrease information asymmetries between management and shareholders (RAPPAPORT, 1998; SCHULTZE ET AL., 2017). Therefore, announcements of downgrades for VBM firms might contain less new information than those for non-VBM firms, leading to weaker capital market reactions. While the prior research mostly finds negative abnormal returns after downgrade announcements, our considerations lead to the following hypotheses:

H1a: The average capital market reaction to the announcement of a rating downgrade is non-negative for VB metric users.

H1b: The capital market reaction to the announcement of a rating downgrade is less negatively associated with the capital market reaction for VB metric users compared to VB metric non-users.

Above, we previously argued that upgrades generally lead to a decreasing cost of debt and may signal a positive development of expected cash flows, which ceteris paribus leads to an increase in shareholder value. However, according to option pricing theory, if upgrades are caused by a decrease of operating or financial risk, this can negatively affect shareholder value. Therefore, management has to trade off the opposing effects on expected returns and the cost of capital and thus on shareholder value. Consequently, we expect that the use of VB performance metrics facilitates decision-making in pursuit of shareholder interests for upgrades as well as for downgrades. Further, VB metrics reduce agency problems. Managers can be assumed to be more risk averse than shareholders due to employment risk (AMIHUD AND LEV, 1981). To maximize their own utility, they choose a level of risk that is lower than the level shareholders would prefer. Using VB metrics can counteract those agency problems because VB metrics clearly demonstrate the effect of management actions on shareholder value and can be used for performance evaluation. Moreover, we expect that investors know that management represents their interests at all times. Thus, we would generally expect a more positive capital market reaction to upgrades of VB metric users. LUEG AND SCHÄFFER (2010) argue that firms with an optimally managed VBM system do not have further potential for improvements and thus for positive abnormal returns. Projecting this argument on an upgrade scenario leads to the prediction of non-existent abnormal returns and weak informational value for rating upgrades of VB metric users.

Prior studies argue that rating agencies announce upgrades in a less timely manner than downgrades because the impact of a late rating change is less severe, or firms tend to communicate ‘good news’ to the market earlier than ‘bad news’ (EDERINGTON AND GOH, 1998; HOLTHAUSEN AND LEFTWICH, 1986; KIM AND NABAR, 2007). Thus, in the case of upgrades, information asymmetries can be assumed to be low or non-existent. As a result, VBM systems and VB reporting, which are instruments to decrease the information asymmetries between management and shareholders, are less relevant in an upgrade context. This leads to the prediction of non-existent abnormal returns to upgrade announcements for VB metric users and non-users alike. We posit our hypotheses accordingly:

H2a: The average capital market reaction to the announcement of a rating upgrade equals zero for VB metric users.

H2b: The capital market reaction to the announcement of a rating upgrade will not differ for VB metric users and non-users.

3 Sample and research design

3.1 Sample

Our initial sample consists of rating changes of firms listed on the HDAX or SDAX (as of December 31, 2011) that are announced[5] during the 1996–2014 period.[6] As rating changes are exogenous and announced by rating agencies independent of the rating subject itself (SCHNABEL, 1996), we obtain those rating changes by accessing the company profiles on Moody's website.[7] Additionally, we verify the announcement date by comparing it to the date of the actual press release by Moody's to address concerns regarding the sensitivity of the event date (BOWMAN, 1983). With respect to the type of rating, we focus on Moody's long-term rating scale and determine a concrete rating change based on the issuer rating or a comparable issue rating.[8] The described procedure results in a total sample of 157 observations (101 downgrades, 56 upgrades). Table 1 presents the sample selection. Due to unavailable stock prices or missing financial data, we exclude three observations. Moreover, we omit three duplicate ratings to avoid biasing the results because a firm is included in the corporate family rating of the parent company (GOH AND EDERINGTON, 1999). After this procedure, 99 downgrades and 52 upgrades remain.

Since the study of HOLTHAUSEN AND LEFTWICH (1986), it has become common practice in the context of rating changes to exclude confounding events from the sample to increase the validity of the statistical tests. This adjustment seems all the more important for large, internationally operating

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5 The announcement date corresponds to the public notification of the rating action itself (MOODY'S INVESTORS SERVICE, 2017).

6 The HDAX comprises the DAX, the MDAX and the TecDAX. Combined with the SDAX, this study focuses on the 130 largest German blue-chip stocks as well as on the 30 largest technology companies by market capitalization and trading volume.

7 Due to the homogeneous practice of the Big 3 with respect to their rating activities, rating changes by Moody's can be considered a representative opinion of the subjects' credit risk (CHUNG ET AL., 2012). There are also several empirical studies that do not find any significant differences in the informational value of rating changes, especially by Moody's and S&P (e.g., HOLTHAUSEN AND LEFTWICH, 1986; LI ET AL., 2006; STEINER AND HEINKE, 2001).

8 To obtain a representative sample, we use the long-term corporate family rating or the (mid-term note) senior unsecured rating in the event that a long-term issuer rating is not available. Due to the generally identical credit rating of a corporate group and its parent company and the fact that long-term issue ratings and the issuer rating are usually equivalent (BANNIER AND HIRSCH, 2010), we ensure comparability.

firms because the capital market reaction to rating changes can be biased by various other types of announcements and information affecting the stock price of the firm (McWilliams and Siegel, 1997). For our sample, which is dominated by DAX firms,[9] we check for confounding events that have been published within a period of two days before and two days after the announcement of the rating change. We identify 36 contaminated observations and exclude them from the analysis.[10] The final sample consists of 72 downgrades and 43 upgrades, which correspond to 38 different German firms.

[Insert Table 1 about here]

Further, we hand-collect data on the use of VB metrics by our sample firms. Following the approach of Lovata and Costigan (2002), Rapp et al. (2011), Firk et al. (2016), and Brück et al. (2017), we searched the corporate annual reports to assess whether a firm uses VB performance metrics as performance indicators and/or as a component of management compensation at the time of the rating change. We define a coding scheme ex ante to ensure consistent coding and mitigate subjectivity bias. Regarding this coding scheme, we require a VB performance metric to not only be mentioned but to be explicitly described as a key metric. Further, we classify a firm as a VB metric user if it uses at least one of the following types of VB metrics: profit-based residual income, cash flow-based residual income, and/or corresponding return ratios, such as the EVA spread and cash flow return on investment spread (Firk et al., 2016; Lovata and Costigan, 2002; Rapp et al., 2011). Further, we consider firms using return on invested capital (ROIC), return on capital employed (ROCE) and other similar measures as VB metric users, but only if they compare these measures with the cost of capital. As the different VB metrics are all based upon the same idea (Armitage and Jog, 1996) and as Ryan and Trahan (2007) have shown, no metric per se outperforms any other VB metric, so we presume homogeneity among these metrics for the subsequent analysis.

As shown in Panel A of Table 2, the sample yields a homogenous picture with respect to value orientation: for 67 observations (58.3%), the market is informed about the adoption of a VBM system

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9 An overview of the number of rating changes per stock index is provided in Panel D of Table 2.

10 Confounding events are identified using firm-specific German press releases from the LexisNexis database. We classify the following news categories as confounding events: merger & acquisition activities (7), increases or buybacks of bonds/loans (7), changed revenue or profit forecasts (6), lawsuits or court decisions (5), staff reductions or short-time work (4), restructuring (4), share emission or buy-back programs (3), divestments (3), changes to the composition of the management board (2), dividend announcements (1), and changes in strategy (1). In some cases, there are several confounding events. Thus, the sum of the stated reasons exceeds the sum of the excluded observations.

at the time of the rating change. Moreover, Panel A of Table 2 indicates a synchronous trend of the number of rating changes compared to the business cycle. Both in 2003 and in 2009, we find partly temporally delayed consequences of the dot-com bubble and the financial crisis. However, the period in between is characterized by a higher proportion of upgrades.[11] The actions of the big rating agencies in years of crisis emphasize their important role, e.g., during the financial crisis.

Panel B of Table 2 describes the distribution and magnitude of the rating changes in a migration matrix. The migration matrix is presented for nine superclasses, which we define as follows: Aaa, Aa = [Aa1, Aa2, Aa3], A = [A1, A2, A3], Baa = [Baa1, Baa2, Baa3], Ba = [Ba1, Ba2, Ba3], B = [B1, B2, B3], Caa = [Caa1, Caa2, Caa3], Ca and C. A total of 69 observations (60.0%) are rating changes within one superclass (presented as a diagonal in bold in Panel B, Table 2), and 46 observations (40.0%) are between-class rating changes. The separating line between Baa and Ba marks the transition from investment to speculative grade. In total, 74 observations (64.3%) are rating changes within the investment grade, 31 observations (27.0%) are rating changes within the speculative grade and for 10 observations (8.7%), we find a reclassification from speculative to investment grade or vice versa. Among all 115 observations, we observe 18 multi-notch rating changes,[12] which we later control for in the multivariate analysis.

Examining the number of rating changes per rating subject in Panel C of Table 2, we find that the 115 rating changes relate to 38 firms. Thus, on average, each rating subject is affected by 3.03 rating changes during the observation period. Firms that are affected by exactly two rating changes account for the highest proportion, with 14 of 38 firms (36.8%). However, there is a meaningful explanation for this pattern. Approximately two-thirds of these firms are listed on the German SDAX or MDAX, and those smaller firms generally tend to request and receive an external rating later than firms listed on the DAX. Panel D of Table 2 shows that 54.8% of the total sample are DAX, 42.6% are MDAX, and 2.6% are SDAX firms.[13] The average year of introduction of an external rating for DAX firms in our sample is in 1999, for MDAX firms 2003 and for SDAX firms 2004.

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[11] BANNIER AND HIRSCH (2010), OTT (2011) and HUNDT (2015) observe a similar trend.

[12] We observe seven multi-notch rating changes within one superclass, ten multi-notch rating changes with a change by one superclass and one multi-notch rating change with a change by more than one superclass.

[13] Pivotal to the allocation of the observations to the corresponding market index is the listing of the firm on the event date in question. We refer to DEUTSCHE BÖRSE GROUP (2017) for an elaborate composition history of the German stock indices.

[Insert Table 2 about here]

3.2 *Research design*

RAPPAPORT (1998) states that “a company’s stock price is the clearest measure of market expectations about its future performance” (RAPPAPORT, 1998, p. 101). Thus, to quantify the effect of a rating change on equity value, prior studies frequently use an event study approach and calculate abnormal returns around the announcement day. The abnormal return represents the difference between the observed stock return and the expected return during a predefined event window (MACKINLAY, 1997). We calculate abnormal returns based on daily stock returns to reliably determine the immediate effect of a rating change. Compared to monthly or annual data, this approach mitigates concerns related to confounding events (HOLTHAUSEN AND LEFTWICH, 1986; MACKINLAY, 1997; MORSE, 1984). For the same reason, we define a narrow event window and check for confounding events (HOLTHAUSEN AND LEFTWICH, 1986). MCWILLIAMS AND SIEGEL (1997) recommend a short interval that still surrounds the relevant event. Accordingly, we choose a symmetric [-1;1] interval (e.g., BANNIER AND HIRSCH, 2010; CHUNG ET AL., 2012; HUNDT, 2015; JORION ET AL., 2005) to account for effects that are caused by an announcement after the close (CAMPBELL ET AL., 1997) or by a leak of information before the opening of the stock market (MACKINLAY, 1997; MCWILLIAMS AND SIEGEL, 1997). In addition to the just-defined interval, we further analyze the isolated performance effect of a rating change on the announcement day ($t = 0$).

We calculate abnormal returns based on the total return indices of the given rating subjects from Thomson Reuters Datastream. To finally compute the abnormal return $AR_{i,t}$ for a given event date, the expected return $E(R_{i,t})$ needs to be subtracted from the actual observed return (CAMPBELL ET AL., 1997):

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

The market model is a well-established standard for calculating the expected returns for a given event window (HUNDT, 2015). Its good suitability compared to alternative and more complex models is repeatedly mentioned in prior studies (e.g., CABLE AND HOLLAND, 1999; CAMPBELL ET AL., 1997). Thus, we estimate the expected returns using market model estimation techniques (e.g., BOWMAN, 1983; CAMPBELL ET AL., 1997; STRONG, 1992):

$$E(R_{i,t}) = \alpha_i + \beta_i * R_{M,t} + \varepsilon_{i,t}$$

where α_i is the intercept, β_i is the systematic risk[14], $\varepsilon_{i,t}$ is the estimation error, and $R_{M,t}$ is the return of the market portfolio. Following BROWN AND WARNER (1985), we separately determine the point estimators of the regression function for every event over an individual estimation period of 250 trading days.[15] Thus, the estimation period [-260;-10] approximately covers an entire trading year and accounts for seasonal variability. Furthermore, the definition implies a correction for non-trading days and hence prevents biased estimates (SCHOLES AND WILLIAMS, 1977).

With respect to the ordinary-least-squares estimators, the market index must be an adequate approximation of the market on the one hand (STEINER AND KLEEBERG, 1991) and has to be interrelated with the analyzed firms on the other hand (HUNDT, 2015). The German CDAX suitably represents the German equity market, since it includes all shares of German firms that are listed in Prime or General Standard (DEUTSCHE BÖRSE GROUP, 2004). As our sample contains HDAX as well as SDAX firms, we use this index as a market proxy for the estimation of the regression coefficients.[16]

In addition to the abnormal returns on the event day $AR_{i,0}$, we compute cumulative abnormal returns over the period [-1;1] surrounding the event date. It holds (CAMPBELL ET AL., 1997):

$$CAR_{i,[-1;1]} = \sum_{t=-1}^{1} AR_{i,t}$$

We test our hypotheses by analyzing the capital market reactions to rating changes of VB metric users and VB metric non-users. We first approach H1a and H2a via univariate tests because they refer to the absolute value of the average capital market reaction to rating changes. The abnormal and cumulative abnormal returns are tested for significance using parametric tests and non-parametric tests. In addition to a two-tailed t-test, we use a two-tailed BOEHMER MUSUMECI AND POULSEN (BMP) (1991) t-test to mitigate concerns regarding event-induced variance and event-date clustering. Further, we use a non-parametric Wilcoxon signed rank test (SR) that is robust in the case of a violation of the normality assumption. For the analysis of group differences, we use a parametric paired two-tailed t-test and

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[14] The intrinsic risk of the market is already captured by using a market index as the reference for the approximation of a market portfolio (BINDER, 1998).

[15] Hence, the chosen estimation period falls within the conventional interval of 100 to 300 days (PETERSON, 1989). By estimating the regression coefficients based on the specified estimation window, we assume that the true parameters are constant and do not vary over time.

[16] The assessment of the market model yields an average coefficient of determination of 0.366 (median 0.372) and a mean $\hat{\beta}$ estimate of 0.977 (median 0.958), where $\hat{\beta}$ is statistically significant for 114 observations (thereof for 112 observations at the 1% level).

a non-parametric Wilcoxon rank sum (RS) test. Second, we estimate multivariate regressions to examine the effect of VBM systems on the capital market reaction to announcements of rating changes (H1b and H2b). Since our sample includes more than one rating change per firm, we use cluster-robust standard errors on the firm level in the regression analysis (FROOT, 1989; ROGERS, 1993; WILLIAMS, 2000). Overall, the following model is used to formally test our hypotheses:

$$\begin{aligned}(C)AR_{i,t} = \; & \alpha + \beta_1 * VBM_{i,t}^{CS} + \beta_2 * VBM_{i,t}^{MC} + \beta_3 * lnDAYS_{i,t} + \beta_4 * GRADES_{i,t} + \\ & \beta_5 * FA_{i,t} + \beta_6 * RS_{i,t} + \beta_7 * lnSIZE_{i,t} + \beta_8 * MTB_{i,t} + \beta_9 * WLOLOR_{i,t} + \\ & \beta_{10} * DELTAlnSIZE_{i,t} + \beta_{11} * DELTAROA_{i,t} + \beta_{12} * DELTAIC_{i,t} + \\ & \beta_{13} * DELTADEBT_{i,t} + \beta_{14} * DELTABETA_{i,t} + \beta_{15} * CRISIS1_{i,t} + \beta_{16} * CRISIS2_{i,t} + \\ & \beta_{17} * FINANCIAL_{i,t} + \beta_{18} * DOWNGRADE_{i,t} + \varepsilon_{i,t}\end{aligned}$$

where t represents the respective event window and i the affected rating subject. The abnormal and cumulative abnormal returns are incorporated as the dependent variable in our multivariate regression model. To measure the influence of VB metric use on the capital market reaction to downgrade and upgrade announcements, we include VBM^{CS} as the main independent variable. The variable will take the value of one if firm i utilizes a VB metric as a performance indicator (value-based control system) at the time of the rating change and zero otherwise.[17] Considering the above derived hypotheses, we expect a significantly positive sign of the regression coefficient for downgrades and a non-significant regression coefficient for upgrades.

To avoid misspecifications, we additionally include several control variables. First, in connection with the earlier discussed forms of VBM intensity, we follow the call of, e.g., RAPP ET AL. (2011), and differentiate between varying degrees of VBM implementation. More precisely, we account for the potential influence of compensation tied to a VB metric while examining the performance effect of rating changes. Because MALMI AND IKÄHEIMO (2003) consider the use of VB performance metrics as a component of management compensation plans to be an indication of genuine VBM adoption, we expect the control variable VBM^{MC} to have a positive sign.

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17 A necessary precondition is that the capital market is informed about the use of a VB metric in the firm's control system at the time of the underlying rating change. Therefore, we double-checked several cases by comparing the event date to the release date of the annual report.

Second, LANDO AND SKØDEBERG (2002) identify that the duration during which a firm stays in a given rating grade is negatively correlated with the probability of a rating change in the same direction as the previous rating change. In theory, a long-lasting classification in a given rating grade can either create a stronger surprise effect or it can merely reflect already adjusted expectations and thus does not come as a surprise to investors at all (BANNIER AND HIRSCH, 2010; JORION ET AL., 2005). We expect the independent variable $lnDAYS$ to shed light on the impact of the duration of the assignment, albeit the sign of the coefficient is unknown a priori (JORION ET AL., 2005). In line with JORION ET AL. (2005) and BANNIER AND HIRSCH (2010), we measure the variable as the natural logarithm of the number of days between two consecutive rating changes in the same direction. For rating changes that are not preceded by a rating change in the same direction or that have not been preceded by a rating change at all, we assign a sufficiently large number to the variable to avoid diluting the empirical results.[18]

Third, the total number of notches can affect the capital market reaction to rating changes (HOLTHAUSEN AND LEFTWICH, 1986; WANSLEY ET AL., 1992). We expect a stronger capital market reaction to multi-notch rating changes than to single-notch rating changes.[19] To account for this, we include the control variable $GRADES$, which quantifies the number of skipped notches in our OLS regression (e.g., BANNIER AND HIRSCH, 2010; HAND ET AL., 1992; JORION ET AL., 2005; STEINER AND HEINKE, 2001; WANSLEY ET AL., 1992). Consistent with HAND ET AL. (1992) and BANNIER AND HIRSCH (2010), we expect the sign to be positive (negative) for upgrades (downgrades).

Fourth, analogue to the approach of HILL AND FAFF (2007) and CHUNG ET AL. (2012) (with regard to the effect of watchlist entries), the control variables FA and RS measure the influence of external rating changes from speculative to investment grade and vice versa. We refer to a firm as a fallen angel (FA) if it loses its investment grade status as a consequence of a downgrade. Conversely, we classify an upgraded firm as a rising star (RS) if it advances to investment grade. According to this definition, only one variable can take the value one at a time; however, both variables can be zero for a rating change within the speculative or investment grade.

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[18] The maximum number of days between two consecutive rating changes in the same direction is 3,315, resulting in a logarithmized value of 8.106. In the main analysis, we set the logarithm of the number of days ($lnDAYS$) to 25 for all rating changes that are not preceded by a rating change in the same direction or that have not been preceded by a rating change at all. We tried alternative values (e.g., 10, 50), but they do not change our inferences. JORION ET AL. (2005) and HOLTHAUSEN AND LEFTWICH, 1986) use a similar procedure.

[19] BANNIER AND HIRSCH (2010) also find a significant influence of the initial rating level. If we add a categorial control variable for the initial rating class (or alternatively dummy variables for each rating class), our results remain robust.

Fifth, the variable $lnSIZE$ quantifies the influence of the firm's size, measured as the natural logarithm of market capitalization at the end of the preceding fiscal year (JORION AND ZHANG, 2010; PURDA, 2007). Sixth, we add the variable MTB in order to control for a firm's market-to-book ratio, which reflects growth potential and can affect the firm's current and future ability to cover capital costs (BANNIER AND HIRSCH, 2010).

Seventh, it is regularly assumed that preceding watchlist or outlook entries have an influence on the strength of the capital market reaction (BANNIER AND HIRSCH, 2010; CHUNG ET AL., 2012; HOLTHAUSEN AND LEFTWICH, 1986; HULL ET AL., 2004; STEINER AND HEINKE, 2001). Further, preceding rating changes by other rating agencies can affect the capital market reaction to rating changes (HAND ET AL., 1992; NORDEN AND WEBER, 2004). Thus, we include the dummy variable $WLOLOR$, which equals one for expected rating changes due to a previously announced watchlist entry or rating outlook going in the same direction. Further, the variable $WLOLOR$ equals one if we observe a rating change by Fitch or Standard & Poor's 60 days prior to the rating change by Moody's (our event date) and both point in the same direction. We obtain watchlist entries and rating outlooks from Moody's website. Rating changes by Standard & Poor's and Fitch are collected by searching the company profiles on the rating agencies' websites.

Further, the financial metrics of the rating subjects can be important influencing factors. On the one hand, financial metrics can signal that a firm's rating is about to change, and thus the rating change does not come as a surprise to the capital market (PURDA, 2007). On the other hand, those metrics can indicate the reason for the rating change, which is essential because a decreasing level of cash flows should be associated with negative abnormal returns, whereas an increase of risk can also be associated with a positive capital market reaction. Thus, we add variables for the one-year change in firm size ($DELTAlnSIZE$), return on assets ($DELTAROA$), interest coverage ($DELTAIC$), total debt-to-assets ratio ($DELTADEBT$), and the beta factor ($DELTABETA$) prior to the rating announcement.

Prior studies investigating capital market reactions to rating changes generally do not control for year and industry fixed effects (e.g., GOH AND EDERINGTON, 1999; HAND ET AL., 1992; HOLTHAUSEN AND LEFTWICH, 1986; JORION ET AL., 2005; PURDA, 2007). Our sample covers 19 years and many industries; however, for some of them, it shows only a small number of observations. Thus, it does not seem meaningful to add dummies for all years and industries in our regression models. Instead, we control for selected industries and years. We include the dummy variable $FINANCIAL$ to control for the effect of financial firms (industry classification benchmark: 8000), including banks and insurance companies, on the capital market reaction to rating change announcements.[20] Rating changes within this highly regulated industry may be of low informational value to investors due to a stricter communication policy or may come as a greater surprise because entity-specific information is withheld prior to a rating change to ensure stability of the regulated sector (SCHWEITZER ET AL., 1992).

Since our sample includes different economic cycles, we add two dummy variables to control for potentially stronger (weaker) capital market reactions to downgrades (upgrades) during economic recessions (HUNDT, 2015; JORION ET AL., 2005). According to the ECONOMIC CYCLE RESEARCH INSTITUTE (2018), there were two recessions in Germany during our investigation period. The first recession, which resulted from the dot-com bubble, lasted from January 2001 to August 2003. For the second recession, the financial crisis, a period from April 2008 to January 2009 is used. Thus, $CRISIS1$ equals one if a rating change is observed during the dot-com crisis and zero otherwise. Further, $CRISIS2$ equals one if a rating change is observed during the financial crisis and zero otherwise.[21]

Further, we include the control variable $DOWNGRADE$, which indicates the direction of the rating change. $DOWNGRADE$ equals one if the observed rating change is a downgrade and zero otherwise. Due to expected diverging market reactions based on the direction of the rating change (BOWMAN, 1983), we additionally formulate two separate models for groups of downgrades and upgrades based on the overall regression model described above (e.g., HOLTHAUSEN AND LEFTWICH, 1986; JORION ET AL., 2005). Hence, the variables FA and RS are only relevant for the respective subsample and the overall model, whereas the variable $DOWNGRADE$ is only reported for the overall model. Our variables are summarized in the Appendix.

4 Results

4.1 Descriptive statistics

Table 3 presents the descriptive statistics of the non-binary (Panel A and B) and binary (Panel C) independent variables. For $lnDAYS$, $lnSIZE$ and $DELTAlnSIZE$, we report the non-logarithmized

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[20] If we exclude all financial firms (n = 18) from our analysis instead of using the control variable $FINANCIAL$, our results remain robust.

[21] We conduct two robustness tests. First, we define two dummy variables based on the crisis periods (dot-com crisis: March 2001 – September 2003; financial crisis: December 2007 – December 2010) as they are defined by HUNDT (2015). Second, we use (price and calendar adjusted) GDP growth (source: Federal Statistical Office) as an independent variable instead of dummy variables for the crisis periods. In both robustness tests, our results are unchanged.

values ($DAYS$, $SIZE, DELTASIZE$) to facilitate the interpretation. Panel A of Table 3 reports that the mean time period between two consecutive rating changes in the same direction is approximately two years (mean: 719 days).[22] Panel B of Table 3 shows a mean value of 677 days for consecutive downgrades and 800 days for consecutive upgrades. For bonds, JORION ET AL. (2005) find a mean time period of 142 days for consecutive downgrades and 308 days for consecutive upgrades. Thus, this observation suggests that issuer ratings are more stable compared to issue ratings. The time period between two consecutive downgrades seems to be smaller than for upgrades. According to FINNERTY ET AL. (2013), this can be attributed to increased monitoring intensity by the rating agencies when ratings drop. However, the difference is not significant. In Panel A of Table 3, the differences between the mean and the median of the variables $DAYS$ (mean: 719 days, median: 468 days) and $SIZE$ (mean: 16 billion €, median: 8 billion €) indicate a right-skewed distribution. There are a few firms with very high market capitalization (e.g., Deutsche Telekom AG) and a few firms with a stable rating over a very long time period. Thus, we logarithmize these two variables in the regression analysis. This heterogeneity is reflected in the subsamples of downgrades and upgrades as well (Panel B of Table 3).

Looking at the descriptive statistics in Panel B of Table 3, we find significant differences between the firm characteristics for the downgrade and upgrade sample. Mean and median market-to-book ratio (MTB) are significantly higher for the subsample of upgrades, which reflects better future growth opportunities for upgraded than for downgraded firms. Mean and median changes in firm size ($DELTAlnSIZE$) and interest coverage ($DELTAIC$) are negative for downgrades and positive for upgrades. Thus, the firm size in the downgrade sample is decreasing, and the ability to cover interest expenses deteriorates. The differences are significantly different from zero. Further, the median increase in profitability ($DELTAROA$) is significantly higher for upgraded firms according to the rank sum test. The mean and median changes in the debt-to-assets ratio ($DELTADEBT$) are negative for upgrades and significantly lower than for downgraded firms, which show positive mean and median changes in the debt-to-assets ratio. Thus, the upgraded firms' leverage generally decreased, while the downgraded firms' leverage increased prior to the rating action. Considering the third quartile of the variable $GRADES$ for all groups (Q_3: 1 notch; untabulated for downgrades and upgrades), we find that the sample is dominated by single notch rating changes.

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22 For 56 observations, the rating change is not preceded by a rating change in the same direction or there is no previous rating change at all. Thus, we code the value of $DAYS$ as missing and exclude these observations from the descriptive statistics in Panel A and B of Table 3. For the multivariate analysis, we use log values of $DAYS$ ($lnDAYS$) and set missing values to 25, as described in Section 3.2.

Panel C of Table 3 reports the distribution of the binary variables. A total of 58.3% of all rating changes, 62.5% of the downgrades and 51.2% of the upgrades, refer to VB metric users (VBM^{CS}). The chi-squared test for independence does not reject the null hypothesis of independence between VBM^{CS} ($p = 0.233$) or VBM^{MC} ($p < 0.731$) and the direction of the rating change. Thus, VB metric users do not seem to be affected by downgrades less or more often compared to non-users of VB metrics. Regarding FA and RS, we find that nearly 9% of all observations are characterized by a reclassification from investment to speculative grade or vice versa. This is broadly in line with FINNERTY ET AL. (2013). Further, we find that there are significantly more downgrades than upgrades during the dot-com crisis ($CRISIS1$) ($p < 0.001$). Because there were no upgrade announcements during the dot-com crisis, we drop $CRISIS1$ in the regression models for the subset of upgrades. Moreover, we observe a significant association between $WLOLOR$ and the type of rating change ($p < 0.001$). A closer analysis shows that downgrades are preceded by watchlist entries significantly more frequently compared to upgrades.

Panel D of Table 3 reports the Pearson and Spearman correlations between the independent variables. The correlation matrix shows a medium correlation between the use of VB metrics in control (VBM^{CS}) and management compensation systems (VBM^{MC}). All variance inflation factors are far below the threshold of 10 (HAIR ET AL., 2010). Thus, there are no indicators for a critical level of multicollinearity.

[Insert Table 3 about here]

4.2 Univariate results

We approach H1a and H2a via univariate tests because they refer to the absolute value of the average capital market reaction to rating changes. Table 4 presents univariate results for abnormal returns (AR_0) and cumulative abnormal returns ($CAR_{[-1;1]}$) with regard to the announcement of rating changes. Panel A reports the results for the total sample and for downgrades and upgrades separately. Panel B presents the results for the subsamples of VB metric users and non-users.

In Panel A of Table 4, the mean (median) AR_0 and $CAR_{[-1;1]}$ are -0.2% (-0.3%), and both are not significantly different from zero in two-tailed[23] tests. An interpretation of these results for the total sample is of only limited value, so downgrades and upgrades should be examined separately. For

[23] We report two-tailed tests throughout the paper.

downgrades, we find that the mean (median) AR_0 is -0.4% (-0.4%) and is significantly different from zero at the 10% level only in a Wilcoxon rank sum test. We also find a negative mean (median) $CAR_{[-1;1]}$ for downgrades that is non-significantly different from zero. For the subsample of upgrades, the mean (median) AR_0 is 0.1% (-0.0%) and is not significantly different from zero. We find similar results for $CAR_{[-1;1]}$. Thus, an upgrade decision seems largely to be based on information about which the capital market is already aware. In summary, the results are in line with prior studies that also find asymmetric market reactions to downgrades and upgrades (e.g., BANNIER AND HIRSCH, 2010; EDERINGTON AND GOH, 1998; HOLTHAUSEN AND LEFTWICH, 1986). This suggests either that rating agencies announce upgrades in a less timely manner than downgrades because the impact of a late rating change is less severe or that firms tend to report 'good news' to the market earlier compared to 'bad news' (EDERINGTON AND GOH, 1998; HOLTHAUSEN AND LEFTWICH, 1986; KIM AND NABAR, 2007).

Panel B of Table 4 shows the market reaction for all rating changes differentiated by VB metric users and non-users (VBM^{CS}). For VB metric non-users ($VBM^{CS} = 0$), we find negative values for AR_0 (mean: -0.8%; median: -0.5%), which are significantly different from zero. We also find negative mean and median values for $CAR_{[-1;1]}$ for VB metric non-users that are non-significantly different from zero. For VB metric users ($VBM^{CS} = 1$), we find positive mean and negative median values for AR_0 and $CAR_{[-1;1]}$, which are all non-significant. For downgrades of VB metric non-users, we find significantly negative AR_0 values (mean: -1.3%; median: -0.7%), with $p = 0.019$ (BMP test) and $p = 0.008$ (SR test), and non-significant $CAR_{[-1;1]}$ values (mean: -0.8%; median: -0.3%). For downgrades of VB metric users, the analysis shows non-significant AR_0 values (mean: 0.1%; median: -0.3%) and $CAR_{[-1;1]}$ values (mean: 0.3%; median: -0.3%). Consequently, H1a, which predicts a non-negative capital market reaction for downgrades of VB metric users, cannot be rejected. The difference between VB metric non-users and users is significant only for the event day, with $p = 0.038$ in a t-test (p-value of RS test: 0.034). Hence, consistent with H1b, the capital market reaction to downgrade announcements is less negative for VB metric users compared to non-users on the event day. For upgrades, we find non-significantly negative mean AR_0 and $CAR_{[-1;1]}$ values for non-users of VB performance metrics and non-significantly positive mean AR_0 and $CAR_{[-1;1]}$ values for users of VB metrics. These results do not reject H2a, which predicts a capital market reaction that is not significantly different form zero for upgrades of VB metric users. H2b predicts no difference in the capital market reaction to the announcements of upgrades. The difference between VB metric non-users and users is not significant for AR_0 and $CAR_{[-1;1]}$. Thus, the results are in line with H2b.

[Insert Table 4 about here]

4.3 Multivariate results

To formally test our hypotheses H1b and H2b, Table 5 presents the results of our multivariate regression analysis. The F-statistics are highly significant for all models. The adjusted R^2 values of the total sample and the downgrade models for the event day (AR_0) are positive and have a satisfactory level (total sample: 12.5%; downgrades: 26.1%) compared to other event studies analyzing rating changes (e.g., BANNIER AND HIRSCH, 2010; HAND ET AL., 1992; HILL AND FAFF, 2007; JORION ET AL., 2005; STEINER AND HEINKE, 2001; WANSLEY ET AL., 1992). The adjusted R^2 values of the $CAR_{[-1;1]}$-models are lower. To facilitate the discussion, we focus on AR_0, as the other models lead to inferentially identical conclusions. As the adjusted R^2 values for all the upgrade models are very low, our conclusions should be viewed with caution. Other studies, e.g., HOLTHAUSEN AND LEFTWICH (1986), also report very low adjusted R^2 values and additionally non-significant F-statistics for upgrades. One reason for the lack of explanatory power of upgrade models in general could be that announcements of upgrades themselves do not reveal any new information to the market. Consequently, we do not observe a significant market reaction and cannot determine any influencing factors subsequent to a rating upgrade. A distortion of our results due to multicollinearity is unlikely because of variance inflation factor (VIF) values ranging between 1.91 and 4.53 for all regression models.

The results for the total sample reveal that the main independent variable VBM^{CS} has a positive effect on the capital market reaction on the event day ($p = 0.024$). Further, we find a significantly negative effect for downgrades ($DOWNGRADE = 1$) ($p = 0.031$).

H1b predicts that the capital market reaction to the announcement of downgrades is significantly more positive for VB metric users. In line with our hypothesis, we find a significantly positive association of VBM^{CS} with AR_0 ($p = 0.005$). When we examine the economic significance of this finding as an abnormal change in shareholder value, we find a mean difference of +319.8 million euros between

VB metric users and non-users for a downgrade.[24] This finding supports our argument that VB performance measures improve managerial decision-making and mitigate information asymmetries. H2b predicts that the market reaction to upgrades will be the same for VB metric users and non-users. In line with our hypothesis, VBM^{CS} has no significant effect on the capital market reaction for the upgrade models.

The coefficient of VBM^{MC} is negative and non-significant for all models. Thus, the capital market reaction does not differ between firms that use VB metrics only as performance indicators and those that also use VB metrics for compensation purposes. Thus, the sophistication of a VBM system seems to be less relevant for shareholders than the implementation of a VBM system per se.

Turning to the other control variables, we find a positive and significant coefficient of RS ($p = 0.004$) for the total sample but a non-significant coefficient for the upgrade model. For regulatory reasons, certain investors are only allowed to invest in firms with investment grade ratings (CHUNG ET AL., 2012; HEINKE, 1998; OTT, 2011). Thus, an advance to investment grade should result in more positive abnormal returns. Contrary to our prediction and the prior literature, we find a significantly positive effect for downgrades into speculative grade (FA). However, we observed very few "fallen angels" in our sample, so this finding should be viewed with caution. The number of rating notches has a significant (negative) effect on the capital market reaction only for the AR_0 model for the total sample and the subsample of downgrades, which is in line with other studies (e.g., JORION ET AL., 2005; WANSLEY ET AL., 1992). Further, firm size ($lnSIZE$) and the number of days between two consecutive rating changes ($lnDAYS$) in the same direction are positively associated with the capital market reactions for downgrades and the $CAR_{[-1;1]}$ model for the total sample. The coefficient of $WLOLOR$, which reflects the existence of prior information through watchlist entries, rating outlooks or prior rating changes by other rating agencies, is only significantly negative for the downgrade model on the event day (AR_0). Moreover, we do not find significant differences between financial and non-financial firms ($FINANCIAL$) for downgrades but do for upgrades in the AR_0 model. The change in firm size ($DELTAlnSIZE$) has a negative effect on abnormal returns in the downgrade models and in the $CAR_{[-1;1]}$ model for the total sample and the subsample of upgrades. Finally, we find significantly

[24] To measure the abnormal shareholder value change, we multiply the coefficient of the independent variable VBM^{CS} by the average market capitalization of the rated firms one day before the event day.

positive coefficients for $DELTABETA$ for the total sample and the downgrade and upgrade AR_0 models. Thus, increasing (decreasing) risk prior to a rating action has a positive (negative) effect on the capital market reaction to rating changes. This is in line with the option pricing theory developed by BLACK AND SCHOLES (1973), which states that increasing risk leads to a transfer of wealth from bondholders to shareholders.

[Insert Table 5 about here]

4.4 Additional analyses

To confirm the robustness of our results, we conduct several additional analyses. First, measurements of the market reaction to a certain event largely depend on the methodological approach (BOWMAN, 1983). Thus, as a robustness test, we apply the four-factor model (CARHART, 1997) using the factor set for Germany provided by BRÜCKNER ET AL. (2015) to estimate the (cumulative) abnormal returns.[25] The results (Table 6) of the regression analysis with the use of the four-factor model continue to support H1b and H2b. Second, to rule out potential effects of outliers, we winsorize all non-binary variables at the 1st and 99th percentile levels. Using these winsorized variables, we obtain inferentially identical results (untabulated). Third, ordinary least square regressions are based on the normality assumption, which is often rejected for stock return data (BROWN AND WARNER, 1985; CHOU, 2004). Thus, as a robustness test, we use bootstrapping, which does not rely on the normality assumption. We use 10,000 replications and resample over firm clusters to generate bootstrapped bias-corrected standard errors and confidence intervals. Because the bias corrected 95th confidence intervals for VBM^{CS} for the total sample and the downgrade models lie in the positive range, while the confidence intervals for the upgrade models include zero (untabulated), our results are robust.

Finally, endogeneity concerns are frequently discussed in prior value-based management and ratings research (e.g., BEDENDO AND SIMING, 2018; FIRK ET AL., 2016; HOGAN AND LEWIS, 2005; KNAUER ET AL., 2017; RAPP ET AL., 2011; RYAN AND TRAHAN, 2007). The adoption of a VBM system is a discretionary decision by a firm's management. Thus, endogeneity might bias the results of studies

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[25] To ensure comparability with the market model used in the main analysis and to take into account the composition of our sample with regard to firm size and index, we use the dataset 'Daily Data – ALL (BP: TOP)' to estimate the firm-specific model parameters. The evaluation of the four-factor model yields a mean coefficient of determination of 0.354 (median 0.348).

that investigate the performance effects of VBM. However, those concerns are less critical for our approach because we analyze rating changes, which are clear defined, exogenous events, rather than the adoption of a VBM system. Prior studies find mixed results with regard to the effect of endogeneity on the performance effects of VBM. HOGAN AND LEWIS (2005) and RYAN AND TRAHAN (2007) focus only on adopters of VB compensation systems and analyze the change in performance before and after the implementation of such a system. Both studies find that endogeneity matters. However, studies that investigate the performance effects of VBM by comparing VB metric users with non-users using multivariate analyses with several control variables, as we do, often do not find significant effects of endogeneity (FIRK ET AL., 2016; KNAUER ET AL., 2017; RAPP ET AL., 2011). Even if endogeneity concerns are less critical to our study, we use nearest neighbor propensity score matching to investigate whether our inferences are affected by endogeneity. We calculate the average treatment effect (ATE) of using VB metrics by taking the mean difference between the observed and the potential shareholder value effect for each subject. The potential shareholder value effect is estimated by using the capital market reaction to a similar subject that received the other treatment level (either use or non-use of VB metrics). Similarity between subjects is determined based on the propensity score, i.e., the probability that a firm uses VB metrics, and is estimated via a probit treatment model. Following HOGAN AND LEWIS (2005), this probit model includes firm size, market-to-book ratio, financial leverage, the volatility of stock returns and geographic diversity (measured as the square root of the number of geographic segments) as independent variables. Further, HOGAN AND LEWIS (2005) predict and find that managers of firms with relatively high residual income are more likely to implement a VBM system, especially when accounting profitability is low. Thus, we additionally add return on assets as a measure of accounting profitability, a dummy variable for high economic profits relative to the industry and the interaction of both to the probit treatment model. For downgrades, we find a significantly positive ATE for AR_0 ($p = 0.003$) as well as for $CAR_{[-1;1]}$ ($p = 0.074$) as an outcome variable. Thus, the capital market reaction to downgrades of VB metric users is significantly more positive, and H1b is supported. For upgrades, the ATE is positive but not significantly different from zero ($p = 0.457$ for AR_0 and $p = 0.190$ for $CAR_{[-1;1]}$), which is in line with H2b.

[Insert Table 6 about here]

5 Conclusion

This study investigates the effect of using VB performance metrics within a firm's control system on rating changes. We conduct an event study and analyze the shareholder value effect of rating changes for VB metric users and non-users. We collect a sample of 115 rating changes (72 downgrades and 43 upgrades) of German HDAX and SDAX firms from 1996 to 2014. Our analysis shows that for non-users of VB metrics, upgrades reveal no new information to investors, whereas investors revise their expectations downward upon downgrades. However, there is no significant capital market reaction to rating downgrades of VB metric users. Further, we find a significantly positive association between the use of VB performance metrics and the capital market reaction to downgrades. Thus, the use of VB performance metrics largely offsets the negative effect downgrades have on the capital market reaction. We attribute this effect to the fact that VB performance measures improve managerial decision-making and mitigate the risks associated with managerial self-interest. Further, the use of VB metrics strengthens investors' trust in management and reduces information asymmetries. Investors believe that management takes their interests into consideration and thus do not react to a downgrade announcement. Likewise, an upgrade does not lead to a significantly positive capital market reaction. An upgrade is either based on information that is already known by the capital market, or investors believe that the use of VB performance metrics results in optimal decisions anyway, and hence, the firm's long-term economic development cannot be improved any further.

Our analysis is subject to important limitations. First, the event study methodology allows several modifications that can influence the results of the analysis (BOWMAN, 1983; MCWILLIAMS AND SIEGEL, 1997; PETERSON, 1989). Second, our inferences might not be generalizable to non-German or small- and medium-sized firms. However, prior studies find that the capital market reaction to rating changes announced by a U.S. based agency such as Moody's are weaker in non-US countries (CHAMBERLAIN AND CHEUNG, 1995; STEINER AND HEINKE, 2001). Thus, the effect might be even stronger in the U.S. Additionally, the methodology that we use to distinguish between VB metric users and non-users is based on a manual analysis of annual reports and assumes that these reports correctly reflect the firm's use of VBM systems. Finally, we focus on using VB metrics for control and compensation systems. Therefore, we only roughly distinguish between different levels of VBM sophistication (BURKERT AND LUEG, 2013).

Future research could try to combine publicly and non-publicly available data (e.g., from surveys) to increase the validity of the VBM dataset and gain a more detailed measure of the use of VBM systems, especially for compensation purposes. Further, HUNDT (2015) criticizes the lack of studies analyzing paired samples to learn more about the differing intensities of capital market reactions to downgrades and upgrades. Therefore, analyzing the effect of a rating change before and after the implementation of a VBM system in combination with a larger overall sample might yield additional insights into the relationship between VBM and rating changes.

Appendix

Variable Definitions

Variable	Definition	Data Source
$(C)AR$	Abnormal return on the event day ($t = 0$) or cumulative abnormal return over the period [-1;1] surrounding the event day.	Calculations based on data from Thomson Reuters Datastream
VBM^{CS}	Control variable that takes the value of 1 if the rating subject employs VB metrics in a value-based control system and the capital market is informed about its use at the time of the rating change (0 otherwise).	Dataset compiled on the basis of firms' annual reports
VBM^{MC}	Control variable that takes the value of 1 if the rating subject ties management compensation to a VB metric and the capital market is informed about the compensation plan at the time of the rating change (0 otherwise).	Dataset compiled on the basis of firms' annual reports
$lnDAYS$	Natural logarithm of the number of days between two consecutive rating changes in the same direction (variable takes the value of 25 if the rating change is not preceded by a rating change in the same direction or there is no previous rating change at all).	Moody's
$GRADES$	Number of skipped notches.	Moody's
FA	Control variable that takes the value of 1 if the rating subject drops out of investment grade (0 otherwise).	Moody's
RS	Control variable that takes the value of 1 if the rating subject enters investment grade (0 otherwise).	Moody's
$lnSIZE$	Natural logarithm of market capitalization (in thousand €) at the end of the preceding fiscal year.	Worldscope (WC08001)
MTB	Market-to-book ratio calculated by dividing market capitalization by common equity.	Worldscope (WC08001; WC03501)
$WLOLOR$	Control variable that takes the value of 1 for expected rating changes (0 otherwise). We define rating changes as expected if the firm is on Moody's watchlist or if Moody's announced a rating outlook prior to the actual rating change. A watchlist or outlook entry in the same direction as the rating change is crucial. Further, we define a rating change as expected if there is a rating change by Fitch or Standard & Poor's 60 days prior to the rating change by Moody's (our event date) and both point into the same direction.	Moody's, Standard & Poor's, Fitch
$DELTAlnSIZE$	Change in $lnSIZE$ for the year prior to the rating change compared to the previous year minus 1.	Worldscope (WC08001)
$DELTAROA$	Change in return on assets (ROA) for the year prior to the rating change compared to the previous year minus 1. ROA is defined as net income divided by total assets.	Worldscope (WC01551; WC02999)
$DELTAIC$	Change in interest coverage (IC) for the year prior to the rating change compared to the previous year minus 1. IC is defined as (operating income + interest expense) divided by interest expense.	Worldscope (WC01251 for non-financial firms; WC01075 for financial firms; WC01250)
$DELTADEBT$	Change in debt-to-assets ratio ($DEBT$) for the year prior to the rating change compared to the previous year minus 1. $DEBT$ is defined as total debt divided by total assets.	Worldscope (WC03255; WC02999)
$DELTABETA$	Change in the beta factor ($BETA$) for the year prior to the rating change compared to the previous year minus 1. $BETA$ is calculated using weekly log returns over the previous 52 weeks with CDAX as the market index.	Thomson Reuters Datastream
$CRISIS1$	Control variable that takes the value of 1 if the rating change is announced between January 2001 and August 2003 (0 otherwise).	ECONOMIC CYCLE RESEARCH INSTITUTE (2018)
$CRISIS2$	Control variable that takes the value of 1 if the rating change is announced between April 2008 and January 2009 (0 otherwise).	ECONOMIC CYCLE RESEARCH INSTITUTE (2018)
$FINANCIAL$	Control variable that takes the value of 1 if the rating subject is a financial firm (industry classification benchmark: 8000).	Datastream (ICBIC)
$DOWNGRADE$	Control variable that takes the value of 1 if the rating change at hand is a downgrade (0 if it is an upgrade).	Moody's

$RMRF$	Difference between the return of the market portfolio and the risk-free rate.	BRÜCKNER ET AL. (2015) ("Daily Data – ALL (BP: TOP)")
SMB	Difference between the return of a mimicking portfolio, which contains stocks of small as well as large companies with respect to market capitalization (small minus big).	BRÜCKNER ET AL. (2015) ("Daily Data – ALL (BP: TOP)")
HML	Difference between the return of a mimicking portfolio, which contains stocks of valuable as well as fast-growing companies with respect to market-to-book ratio (high minus low).	BRÜCKNER ET AL. (2015) ("Daily Data – ALL (BP: TOP)")
WML	Difference between the return of a mimicking portfolio, which contains stocks of successful as well as unsuccessful companies with respect to the return over the past eleven months (winners minus losers).	BRÜCKNER ET AL. (2015) ("Daily Data – ALL (BP: TOP)")

The table summarizes the model variables used. It presents the variable definitions as well as the source of the datasets.

References

Amihud, Y., Lev, B., 1981. Risk Reduction as a Managerial Motive for Conglomerate Mergers. RAND J Econ. 12, 605-618.

Antoniou, A., Guney, Y., Paudyal, K., 2008. The determinants of capital structure: capital market-oriented versus bank-oriented institutions. J Financial Quant Anal. 43, 59-92.

Armitage, H.M., Jog, V., 1996. Economic value creation. CMA Mag. 70, 21-24.

Ashbaugh-Skaife, H., Collins, D.W., LaFond, R., 2006. The effects of corporate governance on firms' credit ratings. J Account Econ. 42, 203-243.

Bannier, C.E., Hirsch, C.W., 2010. The economic function of credit rating agencies: what does the watchlist tell us? J Bank Financ. 34, 3037-3049.

Bedendo, M., Siming, L., 2018. The mitigating effect of bank financing on shareholder value and firm policies following rating downgrades. J Corp Finance. 48, 94-108.

Binder, J.J., 1998. The event study methodology since 1969. Rev Quant Finance Accout. 11, 111-137.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. J Political Econ. 81, 637-654.

Boehmer, E., Musumeci, J., Poulsen, A.B., 1991. Event-study methodology under conditions of event-induced variance. J Financial Econ. 30, 253-272.

Bowman, R.G., 1983. Understanding and conducting event studies. J Bus Finance Account. 10, 561-584.

Brown, S.J., Warner, J.B., 1985. Using daily stock returns: the case of event studies. J Financial Econ. 14, 3-31.

Brück, C., Faltynek, B., Knauer, T., Schwering, A., 2017. Determinants of the adoption and performance effects of value-based management systems in Germany. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3021334. Accessed Dec 07, 2017.

Brückner, R., Lehmann, P., Schmidt, M.H., Stehle, R., 2015. Another German Fama/French factor data set. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2682617. Accessed Dec 19, 2017.

Burkert, M., Lueg, R., 2013. Differences in the sophistication of value-based management: the role of top executives. Manag Account Res. 24, 3-22.

Cable, J., Holland, K., 1999. Modelling normal returns in event studies: a model-selection approach and pilot study. Eur J Financ. 5, 331-341.

Campbell, J.Y., Lo, A.W.-C., MacKinlay, A.C., 1997. The econometrics of financial markets. Princeton University Press, Princeton.

Carhart, M.M., 1997. On persistence in mutual fund performance. J Financ. 52, 57-82.

Chamberlain, T.W., Cheung, C.S., 1995. Tests of the value line ranking system: some international evidence. J Bus Finance Account. 22, 575-585.

Chou, P.-H., 2004. Bootstrap tests for multivariate event studies. Rev Quant Finance Acc. 23, 275-290.

Chung, K.H., Frost, C.A., Kim, M., 2012. Characteristics and information value of credit watches. Financial Manag. 41, 119-158.

Cordeiro, J.J., Kent Jr., D.D., 2001. Do EVA™ adopters outperform their industry peers? Evidence from security analyst earnings forecasts. Am Bus Rev. 19, 57-63.

Deutsche Börse Group, 2004. Information Services: the Indices of Deutsche Börse AG. http://deutsche-boerse.com/dbg/dispatch/en/binary/gdb_content_pool/imported_files/public_files/10_downloads/20_indices_misc/Index+Brochure.pdf. Accessed Feb 22, 2018.

Deutsche Börse Group, 2017. Historical index compositions of the equity- and strategy indices of Deutsche Börse. https://www.dax-indices.com/document/Resources/Guides/Historical_Index_Compositions_20171220.pdf Accessed Mar 02, 2018.

Dichev, I.D., Piotroski, J.D., 2001. The long-run stock returns following bond ratings changes. J Financ. 56, 173-203.

Economic Cycle Research Institute, 2018. Business Cycle Chronologies. https://www.businesscycle.com/ecri-business-cycles/international-business-cycle-dates-chronologies. Accessed Mar 04, 2018.

Ederington, L.H., Goh, J.C., 1998. Bond rating agencies and stock analysts: who knows what when? J Financial Quant Anal. 33, 569-585.

Ederington, L.H., Yawitz, J.B., Roberts, B.E., 1987. The informational content of bond ratings. J Financial Res. 10, 211-226.

Elgharbawy, A., Abdel-Kader, M., 2013. Enterprise governance and value-based management: a theoretical contingency framework. J Manag Gov. 17, 99-129.

Everling, O., Trieu, M.L., 2007. Ratingagenturen weltweit [Rating agencies worldwide], in: Büschgen, H.E., Everling, O. (Eds.), Handbuch Rating [Rating manual]. 2. Ed. Gabler, Wiesbaden, 95-116.

Fama, E.F., French, K.R., 2004. The capital asset pricing model: theory and evidence. J Econ Assoc. 18, 25-46.

Finnerty, J.D., Miller, C.D., Chen, R.-R., 2013. The impact of credit rating announcements on credit default swap spreads. J Bank Finance. 37, 2011-2030.

Firk, S., Schrapp, S., Wolff, M., 2016. Drivers of value creation: the role of value-based management and underlying institutions. Manag Account Res. 33, 42-60.

Fridson, M.S., Garman, M.C., 1998. Determinants of spreads on new high-yield bonds. Financial Anal J. 54, 28-39.

Froot, K.A., 1989. Consistent covariance matrix estimation with cross-sectional dependence and heteroskedasticity in financial data. J Financial Quant Anal. 24, 333-355.

Fruhan, W.E., 1979. Financial strategy: studies in the creation, transfer, and destruction of shareholder value. Irwin, Homewood.

Gleißner, W., Füser, K., 2014. Praxishandbuch Rating und Finanzierung: Strategien für den Mittelstand [Rating and finance practice handbook: strategies for medium-sized firms]. 3. Ed. Vahlen, München.

Goergen, M., Manjon, M.C., Renneboog, L., 2008. Is the German system of corporate governance converging towards the Anglo-American model? J Manag Gov. 12, 37-71.

Goh, J.C., Ederington, L.H., 1993. Is a bond rating downgrade bad news, good news, or no news for stockholders? J Finance. 48, 2001-2008.

Goh, J.C., Ederington, L.H., 1999. Cross-sectional variation in the stock market reaction to bond rating changes. Quart Rev Econom Finance. 39, 101-112.

Griffin, P.A., Sanvicente, A.Z., 1982. Common stock returns and rating changes: a methodological comparison. J Finance. 37, 103–119.

Griffith, J.M., 2004. The true value of EVA. J Appl Sci. 14, 25-29.

Hail, L., Leuz, C., 2006. International Differences in the Cost of Equity Capital: do Legal Institutions and Securities Regulation Matter? J Account Res. 44, 485-531.

Hair, J.F.J., Anderson, R.E., Tatham, R.L., Black, W.C., 2010. Multivariate data analysis. Pearson Education, Upper Saddle River.

Hand, J.R.M., Holthausen, R.W., Leftwich, R.W., 1992. The effect of bond rating agency announcements on bond and stock prices. J Finance. 47, 733-752.

Harris, M., Raviv, A., 1990. Capital structure and the informational role of debt. J Finance. 45, 321-349.

Harris, M., Raviv, A., 1991. The theory of capital structure. J Finance. 46, 297-355.

Heinke, V.G., 1998. Bonitätsrisiko und Credit Rating festverzinslicher Wertpapiere: Eine empirische Untersuchung am Euromarkt [Credit risk and credit rating of fixed-income securities: an empirical investigation for the Euromarket]. Uhlenbruch, Bad Soden am Taunus.

Heinke, V.G., 2000. Shareholder Value und Credit Ratings am Aktienmarkt [Shareholder value and credit rating on the stock market]. Finanz Betrieb. 2, 741-748.

Hill, P., Faff, R., 2007. Do credit watch procedures affect the information content of sovereign credit rating changes? Working Paper. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.192.5897

&rep=rep1&type=pdf. Accessed Dec 19, 2017.

Hirshleifer, D., Thakor, A.V., 1992. Managerial conservatism, project choice, and debt. Rev Financial Stud. 5, 437-470.

Hogan, C.E., Lewis, C.M., 2005. Long-run investment decisions, operating performance, and shareholder value creation of firms adopting compensation plans based on economic profits. J Financial Quant Anal. 40, 721-745.

Holthausen, R.W., Leftwich, R.W., 1986. The effect of bond rating changes on common stock prices. J Financial Econ. 17, 57-89.

Hull, J., Predescu, M., White, A., 2004. The relationship between credit default swap spreads, bond yields, and credit rating announcements. J Bank Financ. 28, 2789-2811.

Hundt, S., 2015. Informationsgehalt von Credit Ratings: Eine empirische Analyse europäischer Aktien- und Anleihemärkte [Information content of credit ratings: an empirical analysis of european stock and bond markets]. Springer Gabler, Wiesbaden.

Ittner, C.D., Larcker, D.F., 2001. Assessing empirical research in managerial accounting: a value-based management perspective. J Account Econ. 32, 349-410.

Jorion, P., Zhang, G., 2010. Information transfer effects of bond rating downgrades. Financial Rev. 45, 683-706.

Jorion, P., Liu, Z., Shi, C., 2005. Informational effects of regulation FD: evidence from rating agencies. J Financial Econ. 76, 309-330.

Kim, Y., Nabar, S., 2007. Bankruptcy probability changes and the differential informativeness of bond upgrades and downgrades. J Bank Finance. 31, 3843-3861.

Kliger, D., Sarig, O., 2000. The information value of bond ratings. J Finance. 55, 2879-2902.

Knauer, T., Silge, L., Sommer, F., 2017. The shareholder value effects of using value-based performance measures: evidence from acquisitions and divestments. Manag Account Res, forthcoming.

Lando, D., Skødeberg, T.M., 2002. Analyzing rating transitions and rating drift with continuous observations. J Bank Financ. 26, 423-444.

Li, J., Shin, Y.S., Moore, W.T., 2006. Reactions of Japanese markets to changes in credit ratings by global and local agencies. J Bank Financ. 30, 1007-1021.

Lovata, L.M., Costigan, M.L., 2002. Empirical analysis of adopters of Economic Value Added. Manag Account Res. 13, 215-228.

Lueg, R., Schäffer, U., 2010. Assessing empirical research on value-based management: guidelines for improved hypothesis testing. J Betriebswirtschaft. 60, 1-47.

MacKinlay, A.C., 1997. Event studies in economics and finance. J Econ Lit. 35, 13-39.

Malmi, T., Ikäheimo, S., 2003. Value based management practices: some evidence from the field. Manag Account Res. 14, 235-254.

McWilliams, A., Siegel, D., 1997. Event studies in management research: theoretical and empirical issues. Acad Manag J. 40, 626-657.

Merton, R.C., 1973. Theory of rational option pricing. Bell J Econ Manag Sci. 4, 141-183.

Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. J Finance. 29, 449-470.

Moody's Investors Service, 2017. Policy for rated entity notification (EU and South Africa). https://www.moodys.com/uploadpage/Mco%20Documents/Policy_for_Rated_Entity_Notification_EUandSouth_Africa.pdf. Accessed Dec 19, 2017.

Morse, D., 1984. An econometric analysis of the choice of daily versus monthly returns in tests of information content. J Account Res. 22, 605-623.

Norden, L., Weber, M., 2004. Informational efficiency of credit default swap and stock markets: the impact of credit rating announcements. J Bank Financ. 28, 2813-2843.

Ott, C., 2011. Der Informationsgehalt von Credit Ratings am deutschen Aktienmarkt: Eine empirische Untersuchung [Information content of credit ratings at the German stock market: an empirical Analysis]. Gabler, Wiesbaden.

Peterson, P.P., 1989. Event studies: a review of issues and methodology. Q J Bus Econ. 28, 36-66.

Purda, L.D., 2007. Stock market reaction to anticipated versus surprise rating changes. J Financial Res. 30, 301-320.

Rapp, M.S., Schellong, D., Schmidt, M., Wolff, M., 2011. Considering the shareholder perspective: value-based management systems and stock market performance. Rev Manag Sci. 5, 171-194.

Rappaport, A., 1998. Creating shareholder value: a guide for managers and investors. 2. Ed. Free Press, New York.

Rogers, W., 1993. Regression standard errors in clustered samples. Stata Technical Bulletin. 3, 19-23.

Ryan, H., Trahan, E., 2007. Corporate financial control mechanisms and firm performance: the case of value-based management systems. J Bus Finance Acc. 34, 111-138.

Scheipers, G., Ameels, A., Bruggeman, W., 2003. Value-based management: control processes to create value through integration, in: Keuleneer, L., Verhoog, W. (Eds.), Recent trends in valuation: From strategy to value. Wiley, Chichester, 87-150.

Schnabel, H., 1996. Die Funktion des Rating für deutsche Industrieunternehmen als Emittenten [The function of rating for German industrial companies as issuers], in: Büschgen, H.E., Everling, O. (Eds.), Handbuch Rating [Rating manual]. Gabler, Wiesbaden, 305-325.

Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. J Financial Econ. 5, 309-327.

Schultze, W., List, T., Schabert, B., Dinh, T., 2017. Economic consequences of implementing and communicating value based management systems. J Bus Finance Account, Forthcoming.

Schweitzer, R., Szewczyk, S.H., Varma, R., 1992. Bond rating agencies and their role in bank market discipline. J Financial Serv Res. 6, 249-263.

Steiner, M., Kleeberg, J., 1991. Zum Problem der Indexauswahl im Rahmen der wissenschaftlich-empirischen Anwendung des Capital Asset Pricing Model [About the problem of index selection in the context of scientific empirical application of the capital asset pricing model]. Die Betriebswirtschaft. 51, 171-182.

Steiner, M., Heinke, V.G., 2001. Event study concerning international bond price effects of credit rating actions. Int J Finance Econ. 6, 139–157.

Stewart, G.B., 1991. The quest for value: The EVATM management guide. HarperBusiness, New York.

Stewart, G.B., 1995. EVA works: but not if you make these common mistakes. Fortune. 131, 117–118.

Strong, N., 1992. Modelling abnormal returns: a review article. J Bus Finance Account. 19, 533-553.

Stulz, R., 1990. Managerial discretion and optimal financing policies. J Financial Econ. 26, 3-27.

Wansley, J.W., Glascock, J.L., Clauretie, T.M., 1992. Institutional bond pricing and informational arrival: the case of bond rating changes. J Bus Finance Account. 19, 733-750.

Weber, J., Bramsemann, U., Heineke, C., Hirsch, B., 2017. Wertorientierte Unternehmenssteuerung: Konzepte – Implementierung – Praxis-Statements [Value based management: concepts – implementation – comments from practice]. Gabler, Wiesbaden.

Williams, R.L., 2000. A note on robust variance estimation for cluster-correlated data. Int Biom Soc. 56, 645-646.

Table 1: Sample selection

		Observations
Observed rating changes of German HDAX and SDAX firms during the period 1996–2014		157
excl.	incomplete stock price or financial data	3
excl.	rating change that refers to a rating subject that is also included in an aggregated corporate group rating (duplicate rating)	3
excl.	contaminated observations due to confounding events	36
Total sample		115
thereof	downgrades	72
thereof	upgrades	43

The table presents the sample selection and composition of the observed rating changes for HDAX and SDAX firms during the period 1996–2014.

Table 2: Sample distribution

Panel A: Distribution of rating changes

	Downgrades		Upgrades		Total		thereof VBM
Year	n	in %	n	in %	n	in %	n
1996	1	1.4	1	2.3	2	1.7	1
1997	1	1.4	0	0.0	1	0.9	1
1998	1	1.4	0	0.0	1	0.9	0
1999	1	1.4	0	0.0	1	0.9	1
2000	2	2.8	0	0.0	2	1.7	0
2001	5	6.9	0	0.0	5	5.2	3
2002	4	5.6	0	0.0	4	3.4	0
2003	10	13.9	0	0.0	10	8.6	7
2004	2	2.8	6	14.0	8	6.9	3
2005	4	5.6	4	9.3	8	6.9	4
2006	1	1.4	1	2.3	2	1.7	1
2007	2	2.8	6	14.0	8	6.9	4
2008	6	8.3	3	7.0	9	7.8	6
2009	14	19.4	1	2.3	15	12.9	12
2010	1	1.4	3	7.0	4	3.4	1
2011	3	4.2	5	11.6	8	6.9	7
2012	5	6.9	4	9.3	9	7.8	5
2013	6	8.3	4	9.3	10	8.6	5
2014	3	4.2	5	11.6	8	6.9	6
Total	72	100.0	43	100.0	115	100.0	67

Panel B: Migration matrix

	New rating								
	Aaa	Aa	A	Baa	Ba	B	Caa	Ca	C
Old rating									
Aaa		3							
Aa		**6**	8						
A		2	**15**	8					
Baa			7	**25**	4				
Ba				5	**17**	2			
B				1	3	**6**	2		
Caa						1			
Ca									
C									
thereof within-class rating changes (in %)									
		54.5	50.0	64.1	70.8	66.7	0.0		

Panel C: Number of rating changes per rating subject

Number of rating changes	1	2	3	4	5	6	≥ 7	Total
Number of rating subjects	8	14	6	2	4	0	4	38
in %	21.1	36.8	15.8	5.3	10.5	0.0	10.5	100

Panel D: Number of rating changes per stock index and average year of implementation of the external rating

Stock index	DAX	MDAX	SDAX	TecDAX	Total
Number of rating changesm	63	49	3	0	115
in %	54.8	42.6	2.6	0.0	100.0
Average year of implementation	1999	2003	2004	-	

Panel A presents the absolute (n) and relative (in %) distribution of rating changes for the given observation period (1996–2014). Presented are the distribution of the total sample as well as the distributions of the groups of downgrades and upgrades. Additionally, the table shows the number of rating changes that refer to firms using a VBM system at the time of the rating action. Panel B shows the observed rating migration for the total sample. For simplification purposes, we aggregate rating grades and define superclasses. We define the superclasses as follows: Aaa, Aa = [Aa1, Aa2, Aa3], A = [A1, A2, A3], Baa = [Baa1, Baa2, Baa3], Ba = [Ba1, Ba2, Ba3], B = [B1, B2, B3], Caa = [Caa1, Caa2, Caa3], Ca and C. The diagonal (bold) shows the number of within-class rating changes, whereas entries deviating from the diagonal describe the number of between-class rating changes. The separation line between Baa and Ba marks the transition from investment to speculative grade. Moreover, the table presents the relative proportion of within-class rating changes based on the entirety of rating changes for a specific superclass (in %). Panel C presents the absolute and relative frequency (in %) of observed rating changes per rating subject for the total sample. Rating subjects that are affected by more than six rating changes during the 1996–2014 period are subsumed under "$\geq$ 7". Panel D presents the absolute and relative frequency (in %) of observed rating changes per stock index as well as the average year of implementation of the issuer rating or the long-term issue rating for the total sample.

Table 3: Descriptive statistics of the independent variables

Panel A: Descriptive statistics of the non-binary independent variables (total sample, $n = 115$)

Variable	$\bar{x}$	Min.	Q_1	Median	Q_3	Max.	SD
$DAYS$ (in days)	718.949	38.000	226.000	468.000	1,067.000	3,315.000	732.258
$GRADES$ (in notches)	1.183	1.000	1.000	1.000	1.000	4.000	0.470
$SIZE$ (in thousand €)	16,499,918	214,616	2,499,150	8,357,808	18,848,092	213,793.887	26,295,701
MTB	1.606	-4.209	0.976	1.515	2.080	6.164	1.044
$DELTASIZE$	0.069	-0.688	-0.266	0.048	0.260	1.782	0.465
$DELTAROA$	-0.678	-69.867	-0.917	-0.113	0.333	21.484	7.283
$DELTAIC$	0.143	-3.500	-0.292	0.021	0.411	6.167	1.080
$DELTADEBT$	0.030	-0.955	-0.131	-0.048	0.099	1.856	0.370
$DELTABETA$	0.018	-11.266	-0.204	0.021	0.246	2.623	1.203

Panel B: Descriptive statistics of the non-binary independent variables differentiated by the direction of the rating change

	Downgrades ($n = 72$)			Upgrades ($n = 43$)				
Variable	$\bar{x}$	Median	SD	$\bar{x}$	Median	SD	t-test	RS test
$DAYS$ (in days)	677.436	321.000	746.316	799.900	675.500	715.832	0.548	0.337
$GRADES$ (in notches)	1.208	1.000	0.442	1.140	1.000	0.516	0.450	0.165
$SIZE$ (in thousand €)	16,617,171	6,680,337	29,973,948	16,303,589	8,793,750	18,920,366	0.951	0.444
MTB	1.473	1.321	0.911	1.828	1.909	1.216	0.078	<0.001
$DELTASIZE$	-0.118	-0.147	0.399	0.383	0.287	0.397	<0.001	<0.001
$DELTAROA$	-1.207	-0.299	9.062	0.208	0.203	1.973	0.315	0.004
$DELTAIC$	-0.035	-0.080	1.065	0.440	0.337	1.052	0.022	<0.001
$DELTADEBT$	0.105	0.016	0.438	-0.095	-0.118	0.143	<0.001	<0.001
$DELTABETA$	-0.035	-0.001	1.464	0.107	0.036	0.542	0.543	0.979

Panel C: Descriptive statistics of the binary independent variables differentiated by the direction of the rating change

	Total (n = 115)		Downgrades (n = 72)		Upgrades (n = 43)		
Variable	n	in %	n	in %	n	in %	χ^2-test
VBM^{CS}	67	58.3	45	62.5	22	51.2	0.233
VBM^{MC}	30	26.1	18	25.0	12	27.9	0.731
FA	4	3.5	4	5.6	0	0.0	-
RS	6	5.2	0	0.0	6	14.0	-
$CRISIS1$	18	15.7	18	25.0	0	0.0	<0.001
$CRISIS2$	8	7.0	6	8.3	2	4.7	0.453
$FINANCIAL$	18	15.7	14	19.4	4	9.3	0.148
$WLOLOR$	98	85.2	68	94.4	30	69.8	<0.001

Panel D: Pearson (top) and Spearman (below) correlations matrix (total sample, $n = 115$)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) VBM^{CS}		***0.50***	-0.02	-0.12	0.06	-0.12	0.01	-0.15	0.00	-0.10	0.11	0.06	0.03	-0.01	-0.07	0.02	-0.07	0.11
(2) VBM^{MC}	***0.50***		-0.08	-0.06	0.10	-0.05	***0.26***	-0.01	-0.14	0.01	0.05	0.10	-0.13	0.00	-0.09	-0.08	-0.09	-0.03
(3) $lnDAYS$	-0.02	-0.01		0.06	-0.09	-0.07	-0.10	0.00	0.02	0.14	0.05	0.08	0.01	-0.12	-0.04	-0.07	-0.03	-0.08
(4) $GRADES$	-0.08	-0.04	-0.03		0.03	0.16	0.18	***-0.24***	0.11	0.11	0.08	0.16	0.05	-0.03	***0.19***	-0.03	***0.24***	0.07
(5) FA	0.06	0.10	-0.06	0.05		-0.04	-0.04	-0.02	-0.05	-0.02	0.01	-0.11	***0.28***	0.03	-0.08	0.13	-0.08	0.15
(6) RS	-0.12	-0.05	-0.04	0.02	-0.04		-0.08	-0.10	0.10	***0.25***	-0.02	**0.19**	-0.13	0.08	-0.10	-0.06	-0.10	***-0.30***
(7) $lnSIZE$	0.02	***0.28***	-0.07	0.16	-0.06	-0.11		***0.25***	-0.12	0.09	0.12	-0.03	0.12	0.05	0.11	***0.20***	0.12	-0.08
(8) MTB	-0.17	-0.01	0.04	-0.13	-0.02	0.10	***0.29***		-0.07	***0.33***	-0.05	0.00	0.10	0.13	-0.07	0.12	-0.12	-0.17
(9) $WLOLOR$	0.00	-0.14	0.04	0.11	-0.05	0.10	-0.13	-0.10		-0.12	0.01	0.02	-0.01	-0.02	0.11	0.02	0.04	***0.34***
(10) $DELTAlnSIZE$	-0.11	-0.02	0.14	-0.01	-0.05	***0.28***	0.02	***0.47***	-0.16		0.02	0.13	-0.06	0.02	***-0.23***	0.02	-0.01	***-0.53***
(11) $DELTAROA$	-0.05	0.02	0.03	0.10	-0.05	-0.03	0.17	***0.26***	-0.09	0.16		0.18	0.00	-0.01	0.14	0.01	0.12	-0.09
(12) $DELTAIC$	0.06	0.13	0.05	0.07	***-0.21***	0.14	0.00	0.11	-0.10	***0.29***	***0.23***		-0.08	0.03	0.02	-0.09	-0.03	***-0.21***
(13) $DELTADEBT$	-0.01	-0.08	0.06	0.10	0.16	-0.17	0.13	0.05	0.13	***-0.31***	-0.05	***-0.30***		0.00	0.00	***0.40***	0.00	***0.26***
(14) $DELTABETA$	-0.09	-0.01	-0.12	-0.13	0.13	0.01	0.05	0.13	-0.07	0.03	0.03	0.01	0.04		***-0.24***	-0.01	0.05	-0.06
(15) $CRISIS1$	-0.07	-0.09	-0.07	***0.27***	-0.08	-0.10	0.10	-0.12	0.11	***-0.28***	0.10	-0.15	0.10	-0.17		-0.12	***0.28***	***0.33***
(16) $CRISIS2$	0.02	-0.08	-0.09	-0.03	0.13	-0.06	***0.22***	***0.20***	0.02	0.01	-0.09	-0.14	0.18	-0.01	-0.12		-0.12	0.07
(17) $FINANCIAL$	-0.07	-0.09	-0.01	***0.33***	-0.08	-0.10	0.13	-0.17	0.04	-0.05	0.18	-0.08	0.14	0.02	***0.28***	-0.12		0.14
(18) $DOWNGRADE$	0.11	-0.03	-0.10	0.13	0.15	***-0.30***	-0.07	***-0.31***	***0.34***	***-0.61***	***-0.27***	***-0.38***	***0.39***	0.00	***0.33***	0.07	0.14	
VIF	1.52	1.71	1.11	1.43	1.20	1.33	1.52	1.54	1.26	1.76	1.13	1.19	1.46	1.15	1.47	1.32	1.25	2.18

Table 3 presents the arithmetic mean ($\bar{x}$), minimum (Min.), maximum (Max.), median (Median), quartiles (Q_1, Q_3), and standard deviation (SD) of the non-binary independent variables for the total sample (Panel A) as well as differentiated by the direction of the rating change (Panel B). For the variables $DAYS$, $SIZE$, and $DELTASIZE$ we report the non-logarithmized values. For the variable $DAYS$, we do not include missing values, which we identified and addressed in Section 3.2 Research design. The p-values for group differences are determined by a common two-tailed t-test and a Wilcoxon rank sum test (RS test) for all variables except $DELTADEBT$, as the Levene test for variance heterogeneity does not find heterogeneity between the groups of downgrades and upgrades for these eight cases. For $DELTADEBT$, the Levene test finds variance heterogeneity; thus, we test group differences using a two-tailed t-test for unequal variances and a Wilcoxon rank sum test (RS test). Panel C reports the absolute (n) and relative frequencies (in %) for the case that the binary variables VBM^{CS}, VBM^{MC}, FA, RS, $CRISIS1$, $CRISIS2$, $FINANCIAL$ or $WLOLOR$ equal one for the total sample, the subsample of downgrades, and the subsample upgrades. If a χ^2 test for independence is applicable, the p-value of this test is reported. Panel D presents Pearson (top) and Spearman (below) correlation coefficients between the independent variables as well as the variance inflation factors (VIF) for the total sample. Numbers in bold and italics reflect significant correlations at the 95% confidence level.

Table 4: Capital market reactions to announcements of rating changes

Panel A: Total sample and differentiation by the direction of the rating change

	Total (n = 115)		Downgrades (n = 72)		Upgrades (n = 43)	
	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$
$\bar{x}$	-0.002	-0.001	-0.004	-0.002	0.001	-0.001
Median	-0.003	-0.003	-0.004	-0.003	-0.000	-0.001
t-test	0.329	0.734	0.197	0.760	0.552	0.885
BMP test	0.360	0.970	0.139	0.733	0.631	0.712
SR test	0.160	0.958	0.067*	0.991	0.837	0.856

Panel B: Total sample differentiated by the direction of rating change and the use of VB metrics

	Total (n = 115)		Downgrades (n = 72)		Upgrades (n = 43)	
	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$
(1) $VBM^{CS} = 1$						
n	67	67	45	45	22	22
$\bar{x}$	0.002	0.004	0.001	0.003	0.004	0.006
Median	-0.002	-0.003	-0.003	-0.003	-0.000	0.002
t-test	0.483	0.443	0.810	0.696	0.218	0.338
BMP test	0.484	0.358	0.866	0.773	0.374	0.282
SR test	0.950	0.446	0.800	0.481	0.615	0.570
(2) $VBM^{CS} = 0$						
n	48	48	27	27	21	21
$\bar{x}$	-0.008	-0.008	-0.013	-0.008	-0.002	-0.008
Median	-0.005	-0.002	-0.007	-0.003	-0.000	-0.002
t-test	0.019**	0.128	0.022**	0.282	0.548	0.287
BMP test	0.028**	0.148	0.019**	0.322	0.692	0.287
SR test	0.022**	0.264	0.008***	0.269	0.768	0.664
(3) Differences (1) - (2)						
t-test	0.024**	0.104	0.038**	0.292	0.181	0.148
RS test	0.067*	0.188	0.034**	0.277	0.610	0.544

Table 4 presents mean ($\bar{x}$) and median (Median) abnormal returns on the event date (AR_0) and cumulative abnormal returns for the event window [-1;1]. We compare (cumulative) abnormal returns for the total sample and separately for downgrades and upgrades (Panel A). Panel B further differentiates these results by users and non-users of VB metrics. (Cumulative) abnormal returns are calculated using standard market model estimation techniques. Significance tests for (cumulative) abnormal returns are based on a two-tailed t-test, a modified t-test (BMP Test) as proposed by BOEHMER ET AL. (1991) and a Wilcoxon signed rank test (SR test). Group differences are tested for significance using a two-tailed t-test and a Wilcoxon rank sum test (RS test). The Levene test for variance heterogeneity does not find heterogeneity between the groups of VB metric users and non-users in all cases. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Factors influencing capital market reactions to the announcements of rating changes

Variable	Total ($n = 115$)		Downgrades ($n = 72$)		Upgrades ($n = 43$)	
	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$
α	-0.037	-0.088**	-0.081	-0.138**	0.002	-0.021
	(0.224)	(0.015)	(0.112)	(0.017)	(0.965)	(0.848)
VBM^{CS}	0.015**	0.019**	0.023***	0.026**	0.011	0.023
	(0.024)	(0.032)	(0.005)	(0.031)	(0.251)	(0.316)
VBM^{MC}	-0.010	-0.013	-0.009	-0.013	-0.007	-0.016
	(0.149)	(0.185)	(0.150)	(0.194)	(0.402)	(0.474)
$lnDAYS$	0.000	0.001*	0.001*	0.001**	-0.000	-0.001
	(0.288)	(0.087)	(0.085)	(0.042)	(0.360)	(0.365)
$GRADES$	-0.012*	-0.006	-0.018**	-0.008	0.001	-0.004
	(0.094)	(0.515)	(0.025)	(0.421)	(0.925)	(0.814)
FA	0.037*	0.034	0.036**	0.034		
	(0.079)	(0.203)	(0.037)	(0.139)		
RS	0.014***	0.026***			-0.003	0.007
	(0.004)	(0.007)			(0.660)	(0.507)
$lnSIZE$	0.003	0.005*	0.006*	0.008**	-0.000	0.002
	(0.155)	(0.058)	(0.064)	(0.033)	(0.886)	(0.658)
MTB	-0.001	0.003	0.004	0.007	-0.001	-0.002
	(0.809)	(0.391)	(0.250)	(0.171)	(0.831)	(0.849)
$WLOLOR$	-0.005	0.003	-0.033*	-0.025	-0.000	0.004
	(0.430)	(0.694)	(0.067)	(0.196)	(0.995)	(0.790)
$DELTAlnSIZE$	-0.066	-0.400***	-0.253**	-0.595***	-0.008	-0.350**
	(0.371)	(0.001)	(0.014)	(<0.001)	(0.917)	(0.040)
$DELTAROA$	-0.000	-0.000	-0.000	-0.000	0.000	-0.002
	(0.331)	(0.464)	(0.325)	(0.450)	(0.970)	(0.600)
$DELTAIC$	-0.001	-0.002	-0.002	-0.003	-0.000	0.002
	(0.598)	(0.698)	(0.475)	(0.605)	(0.987)	(0.697)
$DELTADEBT$	0.004	-0.004	0.004	-0.002	-0.037	-0.018
	(0.707)	(0.652)	(0.573)	(0.843)	(0.109)	(0.710)
$DELTABETA$	0.004***	0.002	0.003**	0.000	0.009*	0.009
	(<0.001)	(0.130)	(0.017)	(0.734)	(0.058)	(0.289)
$FINANCIAL$	0.003	0.001	0.007	0.006	0.018**	0.008
	(0.258)	(0.782)	(0.139)	(0.508)	(0.027)	(0.618)
$CRISIS1$	0.002	0.000	0.000	-0.004		
	(0.543)	(0.955)	(0.965)	(0.615)		
$CRISIS2$	-0.005	-0.036	-0.014	-0.051	-0.006	-0.015
	(0.752)	(0.118)	(0.508)	(0.120)	(0.544)	(0.744)
$DOWNGRADE$	-0.009**	-0.011				
	(0.031)	(0.135)				
$\bar{R}^2$	0.125	0.035	0.261	0.065	-0.018	-0.192
F-test	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
VIF_{max}	2.18	2.18	1.91	1.91	4.53	4.53

Table 5 presents the results of an OLS regression with cluster-robust standard errors at the firm level with the dependent variables AR_0 and $CAR_{[-1;1]}$ for the total sample as well as differentiated by the direction of the rating change. All variable definitions are summarized in the Appendix. This table reports the coefficients of the regressions as well as p-values of the corresponding two-tailed t-test in parentheses below the coefficients. Additionally, the corrected coefficient of determination ($\bar{R}^2$), the p-value of the F-test as well as the maximum variance inflation factor (VIF_{max}) are reported. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Factors influencing capital market reactions to the announcements of rating changes using the four-factor model (CARHART, 1997)

Variable	Total ($n = 115$)		Downgrades ($n = 72$)		Upgrades ($n = 43$)	
	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$	AR_0	$CAR_{[-1;1]}$
α	-0.021 (0.471)	-0.072* (0.051)	-0.062 (0.159)	-0.103* (0.055)	0.010 (0.776)	-0.018 (0.879)
VBM^{CS}	0.013* (0.061)	0.022** (0.012)	0.025*** (0.005)	0.033*** (0.002)	0.005 (0.617)	0.016 (0.523)
VBM^{MC}	-0.008 (0.257)	-0.013 (0.148)	-0.008 (0.177)	-0.014 (0.169)	-0.001 (0.851)	-0.009 (0.698)
$lnDAYS$	0.000 (0.766)	0.000* (0.086)	0.001 (0.218)	0.001** (0.039)	-0.000 (0.263)	-0.000 (0.718)
$GRADES$	-0.009 (0.211)	-0.002 (0.855)	-0.016* (0.057)	-0.006 (0.521)	0.007 (0.280)	-0.006 (0.774)
FA	0.031 (0.203)	0.029 (0.208)	0.030 (0.120)	0.028 (0.102)		
RS	0.012** (0.044)	0.027** (0.021)			-0.004 (0.450)	0.009 (0.457)
$lnSIZE$	0.002 (0.345)	0.003 (0.196)	0.005* (0.076)	0.005 (0.144)	-0.001 (0.420)	0.001 (0.772)
MTB	0.001 (0.628)	0.005 (0.129)	0.006* (0.097)	0.014*** (0.005)	0.003 (0.342)	-0.001 (0.898)
$WLOLOR$	-0.008 (0.188)	-0.000 (0.953)	-0.040* (0.063)	-0.034** (0.036)	0.000 (0.995)	0.007 (0.701)
$DELTAlnSIZE$	-0.116 (0.111)	-0.537*** (<0.001)	-0.315*** (0.003)	-0.825*** (<0.001)	-0.096 (0.203)	-0.351** (0.036)
$DELTAROA$	-0.000 (0.442)	-0.000 (0.496)	-0.000 (0.350)	-0.000 (0.555)	0.000 (0.788)	-0.002 (0.723)
$DELTAIC$	-0.001 (0.620)	-0.004 (0.329)	-0.001 (0.683)	-0.005 (0.441)	-0.002 (0.415)	-0.004 (0.367)
$DELTADEBT$	0.002 (0.815)	-0.013 (0.202)	0.004 (0.600)	-0.011 (0.249)	-0.049** (0.016)	-0.041 (0.433)
$DELTABETA$	0.004*** (<0.001)	0.002 (0.144)	0.002* (0.072)	0.001 (0.714)	0.008** (0.035)	0.002 (0.834)
$FINANCIAL$	0.005 (0.189)	-0.001 (0.835)	0.012* (0.066)	0.012 (0.316)	0.012* (0.091)	-0.007 (0.720)
$CRISIS1$	0.004 (0.340)	0.004 (0.533)	0.001 (0.810)	-0.001 (0.947)		
$CRISIS2$	-0.001 (0.961)	-0.026 (0.206)	-0.013 (0.513)	-0.035 (0.198)	-0.005 (0.671)	-0.027 (0.501)
$DOWNGRADE$	-0.007* (0.089)	-0.010 (0.260)				
$\bar{R}^2$	0.063	0.073	0.236	0.131	-0.042	-0.229
F-test	<0.001***	<0.001***	<0.001***	<0.001***	0.004***	<0.001***
VIF_{max}	2.18	2.18	1.91	1.91	4.53	4.53

Table 6 reports the results of an OLS regression with cluster-robust standard errors at the firm level with the dependent variables AR_0 and $CAR_{[-1;1]}$ for the total sample as well as differentiated by the direction of the rating change. The (cumulative) abnormal returns are calculated using the four-factor model (CARHART, 1997). All variable definitions are summarized in the Appendix. This table reports the coefficients of the regressions as well as p-values of the corresponding two-tailed t-test in parentheses below the coefficients. Additionally, the corrected coefficient of determination ($\bar{R}^2$), the p-value of the F-test as well as the maximum variance inflation factor (VIF_{max}) are reported. The superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.