CREDIT RATING CHANGES & AUDITOR REPORTING ACCURACY

NADINE FUNCKE
Maastricht University
P.O. Box 616, 6200 MD Maastricht
The Netherlands
n.funcke@maastrichtuniversity.nl

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ABSTRACT

This study addresses the question whether credit ratings are associated with auditor reporting accuracy. Given credit rating agencies' private information access, experience and expertise, I examine whether the presence of poor credit ratings and especially credit rating downgrades contain incremental information for auditors' going-concern opinion (GCO) decisions that improve auditors' GCO decisions. Furthermore, I investigate if the association between credit rating downgrades and auditor reporting errors varies as a function of auditor specialization. Based on a sample of financially distressed U.S. public companies with Standard and Poor's credit ratings between 1999 and 2012, I find that poor credit ratings significantly increase Type I errors, but do not decrease Type II errors. However, credit rating changes and particularly more severe and more recent rating downgrades are associated with a higher (lower) probability of Type I (Type II) errors. Finally, I find weak evidence that auditors clearly not specialized in their client's industry are less conservative but that credit rating downgrades reduce their Type II reporting error rate. Overall, the results imply that credit ratings function as external warning signals that increase auditor conservatism.

Keywords: going-concern reporting errors; credit rating (changes); auditor industry specialization

INTRODUCTION

This study investigates the relationship between credit ratings and going concern reporting misclassifications. In addition to the effects of client and auditor characteristics on audit reporting accuracy examined in existing literature, I consider how external factors, more specifically publicly available credit ratings, influence auditors' going concern reporting error rates. Credit ratings are publicly available signals communicating financial difficulties. Funcke (2013) finds that lower grade credit ratings and recent credit rating downgrades are associated with a higher probability of auditors issuing an audit report modified for going concern. However, it is unclear whether credit ratings actually improve audit reporting decisions and result in a decrease of audit reporting misclassifications.

The general public, and particularly financial statement users, expect auditors to provide them with a warning of approaching financial difficulties (Chen & Church, 1996). Although bankruptcy prediction is not the auditors' responsibility (AICPA, 1993), bankruptcies that are not preceded by a going concern report (Type II error), and going concern reports not followed by bankruptcy (Type I error), are often perceived as audit reporting failures (McKeown et al., 1991; Geiger & Raghunandan, 2002). Given the public's perception and the auditors' own associated costs of issuing *ex post* incorrect going concern decisions, auditors have clear incentives to minimize their reporting error rate (Matsumura et al., 1997).[1]

Previous research investigating potential reasons for, and variations in, auditor reporting inaccuracies concentrate on client and auditor characteristics (McKeown et al., 1991; Lennox, 1999). Research has also shown that auditors do not just consider firm-specific information, such as financial ratios and management initiatives, in their going concern assessment, but that they incorporate other, broader aspects, such as news items (Gul & Goodwin, 2010).

[1] See Carson et al. (2013) for a research synthesis about auditor reporting on going-concern uncertainty.

Credit ratings arguably also fall in the category of broader aspects worthy of consideration in going-concern assessments because they aim to reflect a company's ability and willingness to meet its financial obligations in accordance with the terms of those obligations (Standard & Poor's, 2012). Credit rating agencies' (CRAs) professional experience and expertise, use of highly sophisticated models, and access to proprietary firm data (SEC, 2000) result in a highly specialized assessment of underlying firm information.[2] Once issued, credit ratings are monitored and updated as deemed necessary (Standard & Poor's). Credit rating downgrades can therefore be considered independent and reliable indicators of impending financial difficulties and capital market participants value the information content inherent in credit ratings and rating changes (Norden & Weber, 2004; Bannier & Hirsch, 2010).

While Funcke (2013) shows that credit ratings influence auditors' GCO decisions, it is still unknown if that results in more accurate audit opinions. On the one hand, incorporating the information contained in credit ratings into the GCO decision may lead to overall lower audit reporting errors. On the other hand, credit rating downgrades may increase auditor conservatism which likely results in increased Type I and decreased Type II reporting errors. I therefore study whether there is an association between audit reporting errors and the presence of credit ratings. Moreover, I analyze the effect of credit rating changes and expect more severe and more recent rating changes to be particularly informative to auditors.

Additionally, I examine whether informative credit ratings have an influence on the association between audit reporting accuracy and auditor specialization. Previous literature establishes that auditor industry specialists provide higher quality audits resulting in lower

[2] Regulation Fair Disclosure (Reg FD) (SEC, 2000) prevents companies from disclosing private information to market professionals, such as stock analysts, without disclosing the same information publicly. Credit rating agencies used to be exempt from this regulation. However, as a result of the recent financial crisis, credit rating agencies are no longer exempt from Reg FD (effective October 4th, 2010; www.sec.gov).

auditor reporting misclassifications (e.g. Solomon et al., 1999; Carcello & Nagy, 2004). Specialists, arguably, do not need to rely on information conveyed in credit ratings. Non-specialist auditors, however, would likely benefit from the information contained in credit ratings. I therefore argue that the reporting error rate for non-specialist auditors should decrease in the presence of an informative credit rating downgrade, and narrow the performance gap between auditor industry specialists and non-specialists.

Analyzing a sample of financially distressed U.S. firms who were audited between 1999 and 2012 and have long-term issuer credit ratings by Standard & Poor's (S&P) during this time period, I find results consistent with increased auditor conservatism. Specifically, I show that the presence of a non-investment grade credit rating and more severe and more recent credit rating downgrades are positively associated with Type I errors. For firms that eventually declared bankruptcy, there is some evidence of reduced Type II errors. Furthermore, I find weak evidence that the association between credit ratings and audit reporting error rates differs for auditor specialists and non-specialists. In particular, there is some evidence that credit rating downgrades narrow the performance gap in Type II errors between clearly non-specialized auditors and other auditors.

This study extends prior research on audit reporting quality by examining if audit reporting accuracy improves in the presence of publicly available, independent signals of financial distress, more specifically, credit ratings. My findings are relevant for practitioners because the evidence seems to suggest that overreliance on credit rating information can lead auditors to issue lower quality (less accurate) GCOs. These findings might also be interesting for credit rating agencies and their assessment of credit quality of financially distressed firms.

The remainder of this paper is organized as follows. In the next section, I describe the relevant background and develop the hypotheses. Section 3 describes the research design including the sample and empirical models. In section 4, I present the results and sensitivity analyses before section 5 concludes.

BACKGROUND AND HYPOTHESES DEVELOPMENT

Audit Reporting Accuracy

Auditors are required to assess the validity of the assumption that a company will continue to operate in the foreseeable future (PCAOB, 2003).[3] If auditors doubt that a client company will survive the next year, they are required to disclose a modified going concern opinion (GCO). The general public and particularly investors often interpret GCOs as future bankruptcy predictions and expect auditors to provide them with a warning signal of approaching financial failure. Yet, auditors' GCOs are only predictions and might therefore be identified as incorrect *ex post*.

Incorrect GCOs can be classified into Type I and Type II reporting errors. Type I errors occur when auditors issue a GCO and the company does not file for bankruptcy in the following year. This often results in dissatisfied clients who switch auditors, which is associated with loss of future revenues for the auditor. When auditors do not issue GCOs but clients subsequently file for bankruptcy (Type II error), auditors usually face dissatisfied investors suing the auditor which results in high litigation costs. Moreover, audit reporting errors are associated with a loss of reputation which can be quite costly for auditors (Matsumura et al., 1997). Despite these incentives to prevent audit reporting errors, prior research shows that 80-90 percent of U.S. companies receiving a GCO do not file for bankruptcy in the following year, while 40-50 percent of companies filing for bankruptcy in the U.S. did not previously receive a GCO (Carson et al., 2013). Considering these numbers,

[3] Auditing standards explain that foreseeable future is generally the next twelve months beyond the date of the financial statements being audited.

questions arise regarding why GCOs are not more accurate and which determinants help auditors in their going concern assessment.

Studies addressing these questions analyze potential determinants of GCOs and report that financial variables, such as profitability, liquidity, leverage, and default status are important predictors of GCOs (Chen and Church, 1992; Mutchler et al., 1997). Moreover, studies examine how auditor reporting accuracy is affected by differences in auditor characteristics, namely competence and independence – the two key drivers of audit quality (DeAngelo, 1981). Competence is frequently proxied by auditor size or auditor specialization and studies using these measures report a positive association between auditor competence and auditor reporting accuracy (Geiger & Rama, 2006; Bruynseels et al., 2011). Independence has been measured by auditor tenure and several (non-)audit fee-related variables (Geiger & Raghunandan, 2002; Callaghan et al., 2009; Robinson, 2008). Overall, these studies do not find evidence for higher reporting inaccuracies by less independent auditors in the U.S. (Carson et al., 2013).

Besides firm and auditor characteristics, external factors also influence audit reporting error rates. Previous research shows that auditors consider broader aspects in the GCO decision such as economic and industry-wide factors (Gul & Goodwin, 2010; Lindberg & Maletta, 2003) as well as information from the public press and other clients in comparable situations (e.g., Mutchler et al., 1997). Funcke (2013) finds evidence consistent with the argument that credit ratings and rating downgrades are another external piece of information that provides incremental information to auditors. This paper examines whether the information contained in credit ratings helps auditors in their GCO assessment and tests whether audit reporting accuracy varies as a function of credit ratings and rating downgrades.

Credit Ratings

Credit ratings are an overall judgment of an issuer's ability and willingness to meet its financial obligations in accordance with the terms of those obligations (Standard & Poor's, 2012). Since this overall judgment is based on a complex, in-depth analysis of quantitative as well as qualitative information of the rated firm, credit rating agencies (CRAs) summarize their findings in the credit rating, a condensed score ranging from AAA to D (see Figure 1 for the complete rating scale) (Standard & Poor's, 2013).

<<<<< Figure 1 >>>>>

Although credit ratings are neither absolute measures of credit quality nor indications of investment merit, they signal relative credit quality by conveying prospective default probabilities of the rated entities (Standard & Poor's, 2003). Since credit ratings might be influenced by future events and unforeseeable developments, CRAs monitor and reevaluate their credit ratings (Standard & Poor's, 2012). Any events that will likely impact the long-term creditworthiness of the rated entity triggers a rating change, which may occur at any point in time following the initial rating (Standard & Poor's, 2013).[4]

The general public often raises the concern that CRAs fail to provide timely and accurate ratings due to independence issues (e.g., Gul & Goodwin, 2010, Cheng & Neamtiu, 2009). Currently, most CRAs pursue the issuer-pays model in which firms requiring credit ratings are charged with a fee for being provided with the credit rating. This raises concerns that CRAs inflate ratings in order to satisfy their customer and/or be re-employed by that customer

[4] Standard & Poor's (2013) states that they reassess all outstanding credit ratings at least on an annual basis and credit rating changes can result from changes in trends, changes in anticipated risks, unexpected deviations of performance or changes in ratings criteria While a rating change is publicly disclosed, reassessments that did not result in rating changes are not that easily observable.

(Beales & Davies, 2007; Lucchetti, 2008).[5] The agencies respond to this concern that they manage potential conflicts of interest by safeguards like segregating negotiating business terms, conducting credit analyses, and ancillary services (Standard & Poor's, 2012).

Addressing the criticism of inaccurate risk assessment and late rating adjustments, CRAs argue that they attempt to avoid excessive rating volatility while holding the timeliness of ratings at an acceptable level. Standard & Poor's (2013) states that they try to factor in the business cycle and thereby aim at preventing rating reversals. Furthermore, CRAs intend to achieve consistency in the rating scale to ensure rating comparability over time (Standard & Poor's). Rating reversals identified as incorrect *ex post* can be quite costly to market participants and CRAs (Cheng & Neamtiu, 2009), which is why CRAs have strong incentives to prevent them.[6] Hence, they only adjust credit ratings when they expect a long-term impact on the firm's creditworthiness (Standard & Poor's, 2012).

While the assignment of credit ratings is not an exact science, studies of debt default show that lower grade credit ratings are typically correlated with higher default rates and have typically been more volatile than higher grade ratings (Standard & Poor's, 2013). This indicates that credit ratings function as a predictor of approaching financial difficulties. Furthermore, an extensive stream of literature addresses the value of credit ratings to various market players (e.g. Hull et al., 2004; Norden & Weber, 2004) and shows that credit ratings and rating downgrades contain information which is valuable to bond and equity investors (e.g. Holthausen & Leftwich, 1986; Ederington & Goh, 1998). Additionally, several studies

[5] This independence concern is particularly pronounced for firms that issue huge amounts of debt resulting in large profits for rating agencies, for companies that issue debt regularly and are thus in need of repetitive services by CRAs, and for companies that also seek ancillary services from CRAs, e.g., consultancy services (Radley & Marrison, 2003).

[6] Contracting parties face higher costs as a result of frequent rating changes because "many funds include portfolio governance rules that require the fund managers to hold only debt issues with credit ratings above a certain threshold. Volatile and unexpected rating changes therefore force managers to trade at inopportune times. In addition, frequent rating reversals over short periods of time would cause some institutional investors to sell and then repurchase the same debt securities with high frequency, imposing large transaction costs." (Cheng & Neamtiu, 2009, p.109). For the rating agencies, frequent rating reversals or rating reversals identified as incorrect ex post consequently result in high reputational costs.

find that rating actions do not only improve information provision but also function as a monitoring device (Hand et al., 1992; Bannier & Hirsch, 2010).[7]

Development of Hypotheses

Audit Reporting Accuracy and Credit Ratings

As both auditors and CRAs monitor a firm's financial situation, it is not surprising that they use common information (Gul & Goodwin, 2010). Nevertheless, there are some arguments why credit ratings might be useful in the auditors' GCO assessment: First, information processing between auditors and CRAs likely differs.[8] CRAs' evaluations are based on a combination of highly sophisticated models and qualitative assessments by specialized staff with extensive experience and expertise (Standard & Poor's, 2012). They focus on information related to firms' creditworthiness and potentially examine these aspects in more depth than auditors which may allow CRAs to conduct a more thorough analysis from which auditors can benefit.

Secondly, information access between auditors and CRAs might differ. Both auditors and CRAs have access to proprietary firm information. However, some of these documents are only available upon request and auditors and CRAs might request different information. Previous research has, for example, shown that some private firm information, such as minutes of board meetings, new product plans and planned future strategies, is standard material incorporated into CRAs' rating assessment in addition to publicly available firm-specific information and broader economic and industry-wide factors (Ederington & Yawitz,

[7] The information role refers to the "reduction of information asymmetry, incorporating private information without jeopardizing competitive advantages and thereby helping stakeholders to differentiate amongst companies with different levels of creditworthiness. By incorporating and assessing firm (internal) information, CRAs potentially contribute to diminish opportunistic behavior by managers, thereby reducing agency conflicts (monitoring role)." (Gul & Goodwin, 2010)
[8] Simnett (1996) conducts an experiment concerning information processing of auditors and finds that information processing is a limiting factor in determining predictive accuracy of firms' bankruptcy. More generally, previous research has shown differences in information processing between tasks as well as between groups of subjects (e.g., Bonner, 1990; Brown & Solomon, 1991). Based on these studies, it is reasonable to infer that auditors and credit rating agencies also process information differently.

1987; Dhaliwal et al., 2011). Potentially, auditors know that CRAs will request this information and rely on CRAs to save time and billable hours. Private information requests between CRAs and auditors may also differ and credit ratings might therefore contain incremental information for the auditors' GCO assessments.

Thirdly, credit ratings function as an effective governance mechanism (Boot et al., 2006). The monitoring by CRAs reduces the information asymmetry between a firm and its external stakeholders, promotes effective decision making, and limits opportunistic behavior by management (Ashbaugh-Skaife et al., 2006). Overall, this may lead to less ambiguity surrounding information which might decrease the likelihood that auditors will misjudge the validity of the going concern assumption.

Based on these arguments, credit ratings potentially contain incremental information that allows auditors to make more informed decisions. The probability of audit errors should thus decrease in the presence of credit ratings compared to companies that do not have credit ratings, both for Type I as well as Type II errors.[9] On the other hand, poor credit ratings might function as a warning signal to auditors which could increase auditor conservatism. This would lead to more frequent issuance of GCOs and (by default) result in more Type I and less Type II errors. Given these two arguments, I test and predict a non-directional hypothesis for Type I errors and a directional hypothesis for Type II errors:

H1a: Type I audit reporting errors are not associated with the presence of credit ratings.

H1b: Type II audit reporting errors are negatively associated with the presence of credit ratings.

[9] Since the going-concern assessment is most important for financially distressed firms, I focus on poor credit ratings as compared to no credit ratings

Besides the information that is, on average, contained in credit ratings, credit ratings likely differ with respect to informativeness to auditors. I thus test the effect of credit rating changes, more particularly credit rating downgrades, on going-concern reporting errors. Moreover, I examine the impact of more severe and more recent rating downgrades. Stronger downgrades are less ambiguous and might be a stronger signal to auditors. Furthermore, the implications of more severe downgrades might be larger for stakeholders. Downgrade timing is likely to matter to auditors as well because downgrades occurring closer to the audit report signature date potentially have implications for the firm.[10] Additionally, management has less time to take mitigating actions and auditors have less time to verify the causes and potential remedies for the downgrade and its implications. More severe and more recent downgrades might therefore be clear signals helping auditors in their GCO assessment thereby reducing both types of reporting errors. Alternatively, more recent and more informative credit ratings might increase auditor conservatism resulting in a higher propensity to issue GCOs and hence more Type I and less Type II errors. Similar to H1a and 1b, I therefore predict and test a non-directional hypothesis for Type I errors and a directional hypothesis for Type II errors:

H2a: Type I audit reporting errors are not associated with (more severe and more recent) credit rating downgrades.

H2b: Type II audit reporting errors are negatively associated with (more severe and more recent) credit rating downgrades.

Audit Reporting Accuracy, Credit Rating Changes, & Auditor Competence

Empirical evidence shows that audit reporting errors occur more frequently for less specialized auditors (Reichelt & Wang, 2010). If credit ratings indeed contain incremental information for auditors, this likely affects GCO assessments of non-specialized auditors.

[10] For example a reclassification of investment grade to non-investment grade can result in restructuring of debt. This might affect a firm’s investors and potentially also firm performance.

Without the credit rating, less competent auditors have difficulties assessing the situation with the same accuracy as more competent auditors. If, however, CRAs improve the monitoring of the firm and summarize new and relevant information in the credit rating, then less competent auditors can easily incorporate this information in their assessment. Informative credit ratings may therefore narrow the performance gap between more and less competent auditors. This conjecture is formulated and tested by the following hypothesis:

H3: The performance gap between specialist and non-specialist auditors becomes smaller in the presence of poor credit ratings and credit rating changes.

RESEARCH DESIGN

Sample

The sample consists of publicly listed U.S. firms for the years 1999 through 2012. Audit related information is obtained from AuditAnalytics and supplemented with company fundamentals and credit ratings from Compustat and market-related information from CRSP. As in prior literature, the analysis excludes the financial sector (SIC codes 6000-6999) and is restricted to financially distressed companies.[11] The sample is further constrained by missing information needed for the multivariate analyses. Parts of the analyses are limited to a subsample of observations with credit ratings (3,822 firm-year observations) and the analyses considering auditor industry specialization are further reduced due to missing information on Metropolitan Statistical Areas (MSA) necessary to compute local auditor specialists (see Table 1 for the complete sample selection procedure).

<<<<< Table 1 >>>>>

[11] Financial distress is defined as having at least two of the following six distress measures: (i) negative net worth, (ii) negative operating cash flow, (iii) negative operating income, (iv) negative working capital, (v) negative net income or (vi) negative retained earnings (DeFond et al., 2002; Lim & Tan, 2008; Li, 2009)

Empirical Model

Existing literature on the determinants of audit reporting errors uses observable data with respect to the underlying firm situation as well as market measures (e.g. Callaghan et al. 2009; Mutchler et al., 1997; Robinson, 2008). In order to test the hypotheses, I therefore estimate the following logistic regression model:

$$ERROR = \beta_0 + \beta_1\, lnAT + \beta_2\, LEVG + \beta_3\, ROA + \beta_4\, CURRENT + \beta_5\, PLOSS + \beta_6\, lnRET + \beta_7\, VARRES + \beta_8\, LAG + \beta_9\, BIGN + \beta_{10}\, EXCHG + \beta_k\, CRs + \varepsilon \quad (1)$$

where:

ERROR = a binary variable equal to 1 if an audit reporting error occurred, (0 otherwise);

lnAT = the natural logarithm of the firm's total assets at fiscal year-end measured in millions of dollars;

LEVG = the ratio of total debt to total assets, both measured at fiscal year-end in millions of dollars;

ROA = the return on assets, i.e. the ratio of net income over total assets, both measured at fiscal year-end in millions of dollars;

CURRENT = the current ratio, i.e. the ratio of total current assets over total current liabilities, both measured at fiscal year-end in millions of dollars;

PLOSS = indicator variable equal to 1 if the company reports a bottom-line loss in the previous year (0 otherwise);

lnRET = natural logarithm of the firm's annual stock return;

VARRES = the variance of the residual of the market model over the fiscal year;

LAG = reporting lag, defined as the number of days between fiscal year end and the auditor signature date;

BIGN = indicator variable equal to 1 if the audit is performed by one of the Big 4 (Big

5) auditors (0 otherwise);

EXCH = indicator variable equal to 1 if listed on the NASDAQ, New York or American Stock Exchange (0 otherwise);

CRs = representing the vector of the variables of interest (see below).

Given that companies who file for bankruptcy are conceptually different from companies that stay in business, I run equation (1) separately for the bankrupt and non-bankrupt sample. The dependent variable ERROR is therefore equivalent to Type I errors in the non-bankrupt sample and Type II errors in the bankrupt sample. Furthermore, I control for year fixed effects and standard errors are clustered by firm because certain firm effects might be overstated due to repeat observations in the panel data set (Petersen 2009; Gow et al., 2010). This simultaneously corrects for heteroskedasticity and possible correlation within a cluster.

Variables of Interest

As explained above, there are potentially two opposing effects which are likely to influence auditor reporting errors. On the one hand, credit ratings and rating changes can improve the information available to auditors and therefore reduce the ambiguity surrounding the GCO decision, decreasing both Type I and Type II errors. On the other hand, credit ratings and rating changes could function as a warning signal to auditors, thereby increasing auditor conservatism which likely results in an increase (decrease) of Type I (II) errors. Model (1) hence includes the following variables of interest to examine the effect of credit ratings and rating downgrades on audit reporting error rates. The indicator variable *D_JUNK* examines the effect of having a non-investment grade credit rating compared to having an investment grade credit rating or not having a credit rating at all. The indicator variable *D_ CRΔ* is included in the model to control for credit rating changes. In order to see whether differences in audit reporting errors are attributable to down- or upgrades, I include the indicator variables *D_DWN* and *D_UP*. Credit rating severity is examined by an ordinal variable *DWN* where higher values are associated with more severe downgrades. Alternatively, indicator variables for one-notch (*D_1NOTCH*), two-notch (*D_2NOTCH*) or three-or-more notch (*D_3NOTCH*) downgrades are included. The effect of *D_3NOTCH* is expected to be larger than the one of *D_2NOTCH* and the *D_2NOTCH* is expected to be stronger than the one of *D_1NOTCH*. Credit rating downgrade severity is also considered to be larger if credit ratings are downgraded multiple times during the year, captured by *NRQ* which measures the number of quarters a company is downgraded in. I also expect a stronger association for more recent downgrades, and hence include indicator variables for the specific quarter the company received a downgrade in, i.e. *D_FQ1-DFQ4*. *D_FQ1* is equal to one of a company is downgraded in the first fiscal quarter and *D_FQ4* if downgrades occurred during the last fiscal quarter of the year, i.e. most recently.

Assuming credit ratings have incremental value to auditors, I expect that this value is more pronounced for non-specialist auditors since they can use the information provided by the rating agencies and therefore improve their performance. Hence, I include interaction effects of auditor specialization and the variables of interest and expect the performance gap between auditor specialists and non-specialists to narrow. Auditor industry specialization is examined in two different ways. First, I focus on non-specialist auditors. Auditors have to invest resources in order to specialize in a certain industry (Eichenseher & Danos, 1981). There are non-specialized auditors, particularly small audit firms, who have less than 5% market share, who still invest resources in a particular industry because they have a large share of *their* portfolio invested in that particular industry. I therefore define clearly non-specialized auditors (*CNSA5*) as an indicator variable that is equal to one if an auditor's portfolio share is no larger than 5% and interact it with the variables of interest.[12] Secondly, I

[12] An auditor's portfolio share is defines as the ratio of assets audited in an industry in a given MSA in a given year relative to all the assets audited by that auditor in all industries in that MSA in that year.

examine the interaction effects of the variables of interest with auditor specialists and hence include *AIS*, an indicator variable equal to one if auditors audit more than 30% of client's assets in the industry.[13]

Control Variables

Prior research shows that larger companies have stronger negotiation power, deeper pockets and higher capacity to avoid bankruptcy (Reynolds & Francis, 2000). I therefore include the logarithm of total assets (*lnAT*) to control for size and expect it to be negatively (positively) associated with Type I (Type II) reporting errors. Firms' financial health and the associated probability of bankruptcy are controlled for by leverage, return on assets and the current ratio. Higher leverage (*LEVG*) is more likely associated with debt covenant violations (Beneish & Press, 1993; Reynolds & Francis), and therefore predicted to have a positive (negative) coefficient in the non-bankrupt (bankrupt) sample. *ROA* and *CURRENT* on the contrary resemble a firm's profitability and liquidity which are expected to be negatively associated with GCOs[14]. Prior literature has shown that previous year losses (*PLOSS*) are positively associated to the probability of GCOs (Callaghan et al., 2009), translating into a higher probability of Type I errors and a lower probability of Type II errors. GCOs are also expected to be negatively correlated with returns (*lnRET*) and positively correlated with volatility of returns (*VARRES*) (DeFond et al., 2002). Other measures commonly controlled for are *BIGN* since these auditors are commonly more conservative (Callaghan et al., 2009); firms being listed on major stock exchanges, *EXCHG*, because these firms are under more scrutiny by regulatory bodies; and reporting lag (LAG). For the sample of bankrupt firms, I also control for bankruptcy reporting lag (*BRLAG*) because Mutchler et al. (1997) find that the

[13] This is the traditional market share specialization measure commonly used in prior literature (e.g. Hogan & Jeter,1999)
[14] Some prior studies include the Zmijewski Score (1084) as explicit measure of the probability of bankruptcy (e.g. DeFond et al. 2002), but to allow for individual differences amongst the variables included in the composite measure, leverage, ROA and current are included in the model separately.

likelihood of receiving a GCO is lower the longer the period between the audit report date and the bankruptcy filing date.

Some of the analyses also include auditor industry specialization as a control. Consistent with existing literature, auditor industry specialization is measured on the local level, based on Metropolitan Statistical Areas (MSAs) (Ferguson et al. 2003; Francis at al., 2005).[15] I expect a positive coefficient for *AIS* in the non-bankrupt sample and a negative one in the bankrupt sample (Bruynseels et al., 2011). Finally, model (1) includes year dummies to allow for changes in auditor reporting behavior over time.[16]

RESULTS

Descriptive Statistics

Over the entire sample period 466 bankruptcies (2.1%) occurred. Bankruptcy filings varied significantly from year to year with a maximum of 97 in 2000 and a minimum of 12 in 2005. Out of those bankruptcies, 149 companies did not receive a GCO before, which translates into a Type II error rate of 31.97%. Moreover, auditors issued GCOs to 2,333 companies, i.e. 10.81%, who did not subsequently file for bankruptcy.[17] Within the sample of firms with credit ratings (3,822 observations), the Type I and Type II error rates are 3.42% and 33.33%, respectively. B ratings are overall the most common, none of the companies with a Type I error are classified as investment grade (Table 2, Panel A), and companies with a Type II error have barely any CCC, CC or D ratings (Panel B).

<<<<< Table 2 >>>>>

[15] Auditors are considered specialists if they audit at least 30 percent of an industry in a given MSA in a given year (e.g., Numan & Willekens, 2012). Consistent with prior literature, each local market is required to have at least two observations per industry in order to ensure a minimum level of competition (e.g., Cahan et al., 2011).
[16] Geiger et al. (2006) report that auditors are more likely to issue GCOs after January 2002.
[17] Prior literature often states that 80-90% of firms receiving a GCO do not file for bankruptcy in the following year. The sample in this study has 2650 firms that receive a GCO and 2,333, i.e. 88.04% of those do not file for bankruptcy. The sample is therefore consistent with samples examined in prior literature.

Table 3 provides an overview of credit rating changes. While there are 1,105 firm-year observations with downgrades during the fiscal year being audited, there are only 281 upgrades. This is not surprising because the sample is limited to distressed firms. Splitting the sample by bankruptcy, one can see that 80 (29), i.e. 8% (26.6 %) of audit opinions given to firms with downgrades are identified as Type I (Type II) error *ex post*.

<<<<< Table 3 >>>>>

Table 4 addresses downgrade severity and timing. Panel A reveals that there are more Type I and less Type II errors as firms receive more severe downgrades. Both types of errors occur less frequently for companies that are downgraded in multiple quarters during the fiscal year (Panel B). However, Panel C shows that there is no easily detectable pattern of reporting error frequency with respect to downgrade timing.

<<<<< Table 4 >>>>>

Univariate Results

The univariate results in Table 5 reveal that firms in the sample with and without credit ratings have on average $1,148 million in assets which is larger than the average size of firms analyzed in other studies of financially distressed samples. Moreover, 71% of the sample reported a bottom line loss in the previous year and the average leverage ratio is 26%. Average return for the sample is 21% which seems logical since distressed firms are high risk firms. The average lag of time between fiscal year end and the audit report date is 73 days.

<<<<< Table 5 >>>>>

Unreported tests of mean differences between firms with and without a Type I error in the subsample of non-bankrupt firms shows that firms with a Type I error are smaller, are less likely to be listed on a stock exchange, have longer reporting lags, are more prone to bankruptcy and more likely to report bottom line losses in the previous year. Furthermore, they have more leverage, are more likely to report covenant violations, and have lower returns but a higher volatility of returns. Firms with Type I errors are also less likely to obtain credit ratings and if they have credit ratings, credit rating levels are worse and more likely to have recently been downgraded as compared to firms without reporting errors.

Firms with Type II errors on the contrary, are on average larger, have less leverage, lower bankruptcy scores, lower returns and a shorter time lag between the fiscal year end and the audit report date as well as the audit report date and bankruptcy reporting date. While there is no difference in the likelihood to obtain a credit rating for firms with and without Type II errors, those with Type II error have a lower probability of being downgraded. Overall the structural differences between these subsamples increase the difficulty of disentangling whether these differences can be attributed to credit rating characteristics or whether they are just a result of differences in underlying firm characteristics.

The Pearson correlations between the regression variables are presented in Table 6. The results are in general in line with my expectations and except for the variables that are by construction related to each other, all correlations are below 0.6.[18] *D_ CRΔ* is positively (negatively) related with Type I (Type II) error in the non-bankrupt (bankrupt) sample, indicating that companies with credit rating changes are more likely to receive GCOs. This pattern also holds for downgrades (*D_DWN*) and downgrade severity (*DWN*).

<<<<< Table 6 >>>>>

[18] In untabulated results, variance inflation factors are computed and all are well below 4, indicating that there are no multicollinearity issues (Judge et al. 1988).

Multivariate Results

Model 1 and 2 in Table 7 present the base line regressions for GCOs in the non-bankrupt and bankrupt sample, respectively. The pseudo R^2s are 30.4% and 33.5% which indicate that the model explains the GCO decision fairly well. All coefficients are in line with expectations and prior literature and confirm the univariate results. Model 3 and 4 present the regressions controlling for firm-year observations with a poor credit rating as compared to not having a credit rating. The pseudo R^2s are basically unchanged and D_JUNK is not significantly associated with Type I errors. In the bankrupt sample, however, the coefficient of D_JUNK is negative and statistically significant which is consistent with auditors becoming more conservative in the presence of a poor credit rating, therefore issuing more GCOs and hence making less Type II errors (Model 4).

<<<<< Table 7 >>>>>

Table 8 presents the results with respect to credit rating changes and GCOs.[19] While changes in credit ratings (*D_ CRΔ*) are positively associated with Type I errors (column 1), they do not impact the likelihood of Type II errors (column 2). More specifically, rating upgrades are not associated with reporting errors, and downgrades are positively associated only with Type I errors (column 3 & 4).[20] This association is stronger, the larger the magnitude of the downgrade (column 5).

<<<<< Table 8 >>>>>

Table 9 addresses credit rating severity and timing in more detail. The variables of interest in column 1 and 2 are the number of notches a credit rating is downgraded by.

[19] Unreported results for the baseline regression in a subsample of observations with credit ratings show that the R^2s are slightly higher and that all control variables are in line with expectations and prior findings except for leverage which switches signs.

[20] It is not surprising that credit rating upgrades are not significant because there are only very few observations with an upgrade. The variable *D_UP* drops out of the regression in the bankrupt sample due to too few observations.

Column 1 reveals that the association between Type I errors and downgrades is stronger, the larger the magnitude of the downgrade. Untabulated tests show that a one-notch downgrade is statistically different from a two-notch downgrade or a three-or more notch downgrade. This implies that more severe rating downgrades are associated with a higher probability of a Type I error. There is also a positive association between the probability of a Type I error and the number of quarters a firm is downgraded in (Column 3). Moreover, the probability of Type I errors increases with downgrades occurring more recently (Column 5). These results imply that auditors respond more conservatively to more severe and more recent credit rating changes. The probability of Type II errors is significantly lower for firms with three-or-more notch downgrades (column 2) but all other timing and severity measures are not associated with Type II errors.

<<<<< Table 9 >>>>>

Results with respect to auditor specialization are presented in Table 10 and show that CNSA5 and all of its interaction terms with the credit rating and rating downgrade variables are insignificant in the non-bankrupt sample. Yet, the significantly positive coefficient of the main effect in the bankrupt sample implies that clearly non-specialized auditors (CNSAs) are less conservative than other auditors. The interaction effects between the credit rating downgrade variables and CNSA5 are negative and significant, indicating that CNSAs pay attention to publicly available warning signals and issue less GCOs. So, while Type II error rates are higher for CNSAs, they seem to react to credit rating information which reduces the error rate. Type I error rates do not seem to be significantly associated with CNSAs. Untabulated results with respect to specialized auditors reveal that neither the main effects of auditor specialization (AIS) nor any of the interaction effects with the variables of interest are significant. This suggests that specialists do not react differently to credit ratings and rating changes.[21] Taken together, these findings indicate that downgrades generally amplify auditor conservatism but help CNSAs to improve their going-concern assessment for soon to be bankrupt companies.[22]

<<<<< Table 10 >>>>>

Overall, the results from the non-bankrupt sample support the argument that credit ratings are predominantly perceived as warning signals because the propensity to issue GCOs increases, resulting in a higher Type I error rate. Evidence regarding Type II errors is consistent with increased auditor conservatism but fairly limited. While the lack of statistical significance of the credit rating variables in the bankrupt sample could be explained by data limitations, it might also be the case that auditors of the bankrupt sample foresee that their clients will fail and might therefore not be as affected by credit rating information.

Additional Analyses

Alternative AIS Measures

Besides the market share approach applied earlier, local auditor industry specialization has been measured in different ways in existing literature.[23] I therefore check whether the results change when auditor specialization is defined based on an auditors' portfolio share.[24] Untabulated results confirm that all interaction terms with portfolio share specialists are statistically insignificant.[25] This confirms earlier results that the association between poor

[21] In unreported tests, I also test whether specialist and non-specialist auditors react differently to credit rating timing and severity but find no statistically significant differences.
[22] Given the limited number of observations, one should however be careful with drawing inferences from these results.
[23] The market share approach has been criticized for potentially failing to recognize expertise in large and highly competitive industries where each of the major accounting firms generate a significant amount of revenue because each of the larger firms devote significant audit technologies and expertise in these industries (Neal & Riley, 2004). Potentially some or all big N auditors could therefore be considered specialists.
[24] An auditor is considered a portfolio share specialist in an industry if the ratio of clients' assets audited in that industry in a given MSA in a given year relative to all the clients' assets audited in all industries in that MSA in that year by that auditor is larger than 30%.
[25] Besides the market share and portfolio share approaches, I also define specialist as market leader and portfolio leader. The analyses with these alternative specifications are neither significant

credit ratings (rating downgrades) and reporting errors is not different for auditor industry specialists.

Litigation Risk

Prior literature reports that the Private Securities Litigation Reform Act (PSLRA) reduced litigation threats against auditors and resulted in auditors issuing less GCOs while the Sarbanes Oxley Act (SOX) increased auditor litigation concerns (e.g. Myers et al., 2008; Fargher and Jiang 2008). Since litigation seems to be an influential factor in the GCO decision, I re-run all regression equations controlling for litigation risk.[26] Untabulated tests show that the results with respect to the presence of credit ratings are qualitatively similar. However, credit rating downgrades are associated with a lower probability of Type II errors. Additionally, more recent downgrades are associated with a higher probability of Type I errors and a lower probability of Type II errors. These findings confirm earlier results and the argument of increased auditor conservatism as Type I error rates increase while Type II error rates decrease. Controlling for litigation risk does not affect the results with respect to CNSAs or auditor specialists.[27]

Bankruptcy Probability & Default Status

Existing evidence in the literature indicates that a firm's bankruptcy probability is a relevant factor in the GCO decision. While model (1) controls for potential bankruptcy by including leverage, the return on assets and the current ratio, I replace those variables with the Zmijewski score as a robustness check and find that the results hold.[28]

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[26] High and low litigation risk industries are identified in line with prior research (e.g. Hogan & Jeter, 1999): I include chemicals and allied products, industrial and commercial machinery and computer equipment, electronic and other electrical equipment and components, except computer equipment and business services in the high litigation risk industries, i.e. the two-digit sic codes 28, 35, 36 and 73. Low litigation risk industries are the retail trade industries (two digit sic codes 52-59).

[27] Another commonly controlled for industry group are regulated industries. In separate analyses I rerun all regressions controlling for regulated industries and find qualitatively similar results to those presented in the main section.

[28] The Zmijewski Score (1984) is a bankruptcy prediction model incorporating the fact that financial information for distressed firms is often missing. The coefficients are also adjusted for the common mistake of oversampling distressed firms.

Firm defaults are also related to firm bankruptcy and previous literature finds a positive association between defaults and GCOs. The credit rating variables already control for payment default since a D rating is assigned if a firm is currently in payment default.[29] In order to ensure that the results presented earlier are not driven by D ratings, i.e. payment defaults, the analyses are re-run based on a sample excluding all observations with D ratings. The results (not tabulated for brevity) remain qualitatively unchanged.[30] Besides payment default, technical default might also influence the propensity of reporting errors. I therefore include a variable controlling for technical default, i.e. covenant violations, in the analyses. The results are also qualitatively similar.[31]

Investment Grade Credit Ratings & Credit Rating Upgrades

Since the dataset is limited to financially distressed companies, the number of observations with investment grade credit ratings and credit rating upgrades are very limited and have almost no variation. I therefore rerun all analyses, first based on a sample excluding all investment grade credit ratings and secondly eliminating all credit rating upgrades in order to ensure that the results are not biased due to these observations. For both robustness tests, I find that the results are qualitatively similar.

Regulation Fair Disclosure (RegFD)

The results reported above are based on a sample from 1999-2012. RegFD, which allowed firms to share private information with credit rating agencies without publicly disclosing it to other market participants, was only effective from August 15th, 2000 until

[29] This rating category is thus conceptually different as all other rating categories are based on predictions and not actual outcomes.

[30] As an alternative I include an indicator variable for D credit ratings in all regressions. The results are still qualitatively unchanged. However, this approach does not work in all regression models, I therefore prefer excluding all observations with D ratings.

[31] Covenant violations are manually collected from the firms' annual reports.
The directions of the coefficients are mostly unchanged but results are less significant when controlling for technical default, especially the results with respect to downgrade severity and timing.

October 4th, 2010. I therefore examine whether the results change for samples restricted to the RegFD sub-period.[32] Unreported results do not reveal any qualitative differences.

SUMMARY AND CONCLUSION

This paper examines the association between credit ratings and going-concern reporting errors. Auditor's GCO decisions require a large degree of professional judgment and the general public often views the accuracy of the audit report as a signal of audit quality. Given the uncertainty surrounding the GCO decision, it seems therefore likely that auditors use publicly available information, like credit ratings, that might help them in their GCO assessment. On the one hand, credit ratings potentially contain additional information that is useful to auditors, thereby reducing the ambiguity surrounding the GCO decision. On the other hand, credit ratings might confirm auditors own assessment and function as a warning signal, thereby increasing auditor conservatism which would most likely increase Type I errors and decrease Type II errors. It is therefore an empirical question whether and how audit reporting errors are associated with credit ratings and credit rating changes.

The main findings of this paper coincide with the conservatism argument: The probability of Type I reporting errors is higher for firms that have speculative grade ratings, have been downgraded and that had more severe and more recent downgrades, while the probability of Type II errors is lower for firms with more severe rating downgrades. Controlling for litigation risk, the results become more pronounced, i.e. Type I error rates increase while Type II error rates decrease. Furthermore, clearly non-specialized auditors seem to be generally less conservative, seem to pay more attention to publicly available credit ratings and issue more GCOs as a result of rating changes as compared to other auditors. The associations

[32] Since I need credit rating changes during the fiscal year for which the audit opinion is issued, I limit the sample to firm-year observations with the signature date between August 15th, 2001 and October 4th, 2010. The analyses are run without fixed year effects in order to prevent additional loss of observations

between credit ratings and audit reporting errors do not vary as a function of auditor specialists. Based on these results, it is questionable whether specialists are indeed better or whether they are just more concerned about their reputation and therefore more conservative.

The results of this paper are subject to a number of limitations. First, while I am able to show an association between reporting errors and credit rating information, I face an endogeneity concern as I am unable to disentangle whether auditors derive (part of) their information from credit ratings or whether both GCOs and credit ratings are driven by the same underlying information and just released at different points in time. Second, the sample is severely limited by the necessary overlap of audit information and credit ratings in the financially distressed sample. Third, given regulatory changes as a result of the recent financial crisis, the sample period is not necessarily generalizable to current or future settings. Finally, the analyses focus on credit ratings by Standard and Poor's and there might be variations with respect to other rating agencies.

In conclusion, this study shows that there is a strong association between auditor reporting error rates and credit ratings. The significant associations support the theory that auditors perceive credit ratings as warning signals and therefore become more conservative. This finding is interesting for the profession since it seems that relying on external sources potentially increases audit reporting errors which are quite costly for auditors. Moreover, market participants may find this outcome interesting as they might become more careful with respect to interpreting public warning signals. The results are potentially also interesting for CRAs and their assessment of credit quality of financially distressed firms.

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APPENDIX

Variable Definitions

ERROR = a binary variable equal to 1 if auditors GCO turned out wrong ex post (else 0);

D_CR = an indicator variable equal to 1 if the company has a credit rating outstanding (0 otherwise);

D_JUNK= an indicator variable equal to 1 if the assigned credit rating is speculative grade, i.e. BB^{+} or lower (otherwise 0);

D_INV = an indicator variable equal to 1 if the assigned credit rating is investment grade, i.e. BBB^{-} or higher (otherwise 0);

BB, B, etc.= indicator variables for the individual credit rating levels;

CRL = an ordinal variable ranging from 1 to 10, representing the credit rating level outstanding at the audit report signature date;

D_CRΔ = an indicator variable equal to 1 if a credit rating change occurred during the fiscal year (0 otherwise);

D_DWN = an indicator variable equal to 1 if a credit rating downgrade occurred between the beginning of the fiscal year and the signature date (0 otherwise);

DWN = an ordinal variable representing the number of notches that a company has been downgraded between the beginning of the fiscal year and the auditor signature date;

D_1NOTCH = an indicator variable equal to 1 if a company has been downgraded by one notch between the beginning of the fiscal year and the signature date (0 otherwise);

D_2NOTCH = an indicator variable equal to 1 if a company has been downgraded by two notches between the beginning of the fiscal year and the signature date (0 otherwise);

D_3NOTCH = an indicator variable equal to 1 if a company has been downgraded by three or more notches between the beginning of the fiscal year and the signature date (0 otherwise);

D_Q1 = an indicator variable equal to 1 if a firm has been downgraded in the first quarter of the fiscal year being audited (0 otherwise);

D_Q2 = an indicator variable equal to 1 if a firm has been downgraded in the second quarter of the fiscal year being audited (0 otherwise);

D_Q3 = an indicator variable equal to 1 if a firm has been downgraded in the third quarter of the fiscal year being audited (0 otherwise);

D_Q4 = an indicator variable equal to 1 if a firm has been downgraded in the last quarter of the fiscal year being audited (0 otherwise);

NRQ = an ordinal variable indicating in how many quarters of the year being audited a company received a credit rating downgrade;

CNSA5 = an indicator variable equal to 1 if the auditor is clearly not specialized in an industry (0 otherwise);

AIS = an indicator variable equal to 1 if the auditor is considered to be an industry specialist (0 otherwise).

Variable Definitions (continued)

lnAT =	the natural logarithm of the firm's total assets at fiscal year-end measured in millions of dollars;
LEVG =	the ratio of total debt to total assets, both measured at fiscal year-end in millions of dollars;
ROA =	the return on assets, i.e. the ratio of net income over total assets, both measured at fiscal year-end in millions of dollars;
CURRENT =	the current ratio, i.e. the ratio of total current assets over total current liabilities, both measured at fiscal year-end in millions of dollars;
PLOSS =	indicator variable equal to 1 if the company reports a bottom-line loss in the previous year (0 otherwise);
lnRET =	natural logarithm of the firm's annual stock return;
VARRES =	the variance of the residual of the market model over the fiscal year;
LAG =	reporting lag, defined as the number of days between fiscal year end and the auditor signature date;
BIGN =	indicator variable equal to 1 if the audit is performed by one of the Big 4 (Big 5) auditors (0 otherwise);
EXCH =	indicator variable equal to 1 if listed on the NASDAQ, New York or American Stock Exchange (0 otherwise);
BRLAG =	Bankruptcy reporting lag, defined as the number of days between the audit report date and the bankruptcy date;
D_UP =	an indicator variable equal to 1 if a firm received a credit rating upgrade during the fiscal year being audited (0 otherwise);
UP =	an ordinal variable representing the number of notches that a company has been upgraded between the beginning of the fiscal year and the auditor signature date.

FIGURES

Figure 1: General Summary of the Opinions Reflected by S&P's Ratings (S&P 2012)

Investment Grade	**AAA**	Extremely strong capacity to meet financial commitments. Highest rating
	AA	Very strong capacity to meet financial commitments
	A	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances
	BBB	Adequate capacity to meet financial commitments, but more subjective to adverse economic conditions
	BBB$^-$	Considered highest investment grade by market participants
Speculative Grade	**BB$^+$**	Considered highest speculative grade by market participants
	BB	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions
	B	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments
	CCC	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments
	CC	Currently highly vulnerable
	C	A bankruptcy petition has been filed or similar actions taken. But payments of financial commitments are continued
	D	Payment default on financial commitments

Ratings from 'AA' to 'CCC' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the major rating categories.

TABLES

Table 1: Sample Selection Procedure

Initial sample		104,614
Eliminate all prior 1999	-376	
Eliminate all fin non-distressed	-48,428	
Eliminate financial sector	-11,252	
Eliminate all observations with missing control variables	-22,520	
Basic sample for analyses		**22,038**
Less observations without credit ratings	-18,216	
Final sample for credit rating level analysis		**3,822**
Less observations with missing AIS info	-807	
Final sample for auditor specialization analyses		**3,015**

Table 2: Overview of Credit Rating Levels by Going-Concern Status

	Panel A: Non-Bankrupt Sample			Panel B: Bankrupt Sample		
CR Level	**No GCO**	**GCO**	**Total**	**No GCO**	**GCO**	**Total**
AA	9	0	9			
A	162	0	162			
BBB	536	0	536	2	1	3
BB	973	1	974	7	3	10
B	1,667	35	1,702	30	17	47
CCC	183	40	223	7	32	39
CC	11	7	18	0	11	11
D	14	43	57	1	30	31
Total	3,555	126	3,681	47	94	141

Table 3: Overview of Rating Changes

	Panel A: Non-Bankrupt Sample			Panel B; Bankrupt Sample		
Rating Changes	**No GCO**	**GCO**	**Total**	**No GCO**	**GCO**	**Total**
Upgrades	278	2	280	1	0	1
Downgrades	916	80	996	29	80	109
Total Changes	1194	82	1276	30	80	110
Total Sample	3,300	121	3,421	47	88	135

Table 4: Overview of Downgrade Timing and Severity

Panel A: Downgrade Severity

	Non-Bankrupt Firms						Bankrupt Firms					
	No GCO		**GCO**		**Total**		**No GCO**		**GCO**		**Total**	
1NOTCH_DWN	541	97.48%	**14**	**2.52%**	555	100.00%	**12**	**54.55%**	10	45.45%	22	100.00%
2NOTCH_DWN	234	94.74%	**13**	**5.26%**	247	100.00%	**12**	**54.55%**	10	45.45%	22	100.00%
3NOTCH_DWN	141	72.68%	**53**	**27.32%**	194	100.00%	**5**	**7.69%**	60	92.31%	65	100.00%
Total	916	91.97%	**81**	**8.13%**	996	100.00%	**29**	**26.61%**	80	73.39%	109	100.00%

Panel B: Repeated Downgrades

	Non-Bankrupt Firms						Bankrupt Firms					
	No GCO		**GCO**		**Total**		**No GCO**		**GCO**		**Total**	
DWN in 1Q	733	94.46%	**43**	**5.54%**	776	100.00%	**19**	**33.93%**	37	66.07%	56	100.00%
DWN in 2Q	166	86.91%	**25**	**13.09%**	191	100.00%	**9**	**22.50%**	31	77.50%	40	100.00%
DWN in 3Q	29	85.29%	**5**	**14.71%**	34	100.00%	**1**	**9.09%**	10	90.91%	11	100.00%
DWN in 4Q	2	28.57%	**5**	**71.43%**	7	100.00%	**0**	**0.00%**	1	100.00%	1	100.00%

Panel C: Downgrade Timing

	Non-Bankrupt Firms						Bankrupt Firms					
	No GCO		**GCO**		**Total**		**No GCO**		**GCO**		**Total**	
DWN_FQ4	294	89.09%	**36**	**10.91%**	330	100.00%	**11**	**17.19%**	53	82.81%	64	100.00%
DWN_FQ3	274	88.96%	**34**	**11.04%**	308	100.00%	**10**	**20.41%**	39	79.59%	49	100.00%
DWN_FQ2	299	91.16%	**29**	**8.84%**	328	100.00%	**8**	**22.86%**	27	77.14%	35	100.00%
DWN_FQ1	309	90.35%	**33**	**9.65%**	342	100.00%	**11**	**39.29%**	17	60.71%	28	100.00%

Table 5: Univariate Statistics

Variable	N	Mean	S.D.	Min	Mdn	Max
Type I	22038	0.11	0.31	0	0	1
Type II	22038	0.01	0.08	0	0	1
lnAT	22038	4.96	1.96	0	4.73	10.1
AT	22038	1148.66	3577.66	0	112.66	24417.58
LEVG	22038	0.26	0.38	0	0.15	7.66
ROA	22038	-0.36	1.25	-46.31	-0.12	0.47
CURRENT	22038	3.35	4.62	0	1.91	37.01
PLOSS	22038	0.71	0.46	0	1	1
lnRET	22038	-0.28	0.95	-3.44	-0.2	3.4
VARRES	22038	0	0	0	0	0.03
LAG	22038	72.82	37.49	19	71	392
BIGN	22038	0.73	0.44	0	1	1
EXCH	22038	0.71	0.45	0	1	1
BRLAG	465	112.57	117.82	-549	123	299
D_CR	22038	0.18	0.39	0	0	1
CRL	3822	5.5	1.21	2	6	10
D_ CRΔ	3754	0.42	0.49	0	0	1
DWN	1105	2.24	2.22	1	1	15
UP	281	1.56	1.55	1	1	11

Table 6: Spearman Correlations

	ERROR	lnAT	AT	LEVG	ROA	CURRENT	PLOSS	lnRET	VARRES	LAG	BIGN	EXCH	BRLAG	AIS	CRL	D_ CRΔ	DWN	UP
ERROR		0.2336*	0.2336*	-0.3053*	0.4029*	0.4417*	-0.1421	0.3867*	-0.4266*	-0.3992*	0.0231	-0.0109	0.5912*	0.1210	-0.5662*	-0.3368*	-0.5423*	0.1182
lnAT	-0.0946*		1.0000*	-0.2902*	0.1955*	0.1534	-0.0383	-0.0398	-0.2450*	-0.2219*	0.2270*	0.3350*	0.1334	0.2904*	-0.1426	0.0326	0.0296	0.0155
AT	-0.0946*	1.0000*		-0.2902*	0.1955*	0.1534	-0.0383	-0.0398	-0.2450*	-0.2219*	0.2270*	0.3350*	0.1334	0.2904*	-0.1426	0.0326	0.0296	0.0155
LEVG	0.0236	-0.2712*	-0.2712*		-0.4447*	-0.3768*	0.2613*	-0.3269*	0.4193*	0.4283*	-0.0361	-0.0537	-0.3333*	-0.2937*	0.3583*	0.0677	0.2040*	0.0865
ROA	-0.1546*	0.1752*	0.1752*	0.0459*		0.1954*	-0.1815*	0.5449*	-0.5829*	-0.3693*	0.0465	0.1086	0.3281*	0.1586	-0.3883*	-0.1	-0.2831*	0.1197
CURRENT	-0.1233*	-0.2393*	-0.2393*	-0.1900*	-0.2884*		-0.0967	0.1848*	-0.2551*	-0.3918*	-0.0193	0.0609	0.4592*	0.1276	-0.4818*	-0.2853*	-0.4941*	0.0244
PLOSS	0.0956*	-0.1737*	-0.1737*	0.1419*	-0.2775*	0.1182*		-0.1465	0.2152*	0.0214	0.0279	-0.1796*	-0.2061*	-0.0125	0.3164*	-0.0007	0.088	0.0482
lnRET	-0.1410*	0.0399*	0.0399*	0.0108	0.3304*	-0.0583*	0.0756*		-0.6026*	-0.3679*	0.051	0.0256	0.3339*	0.1143	-0.3614*	-0.2354*	-0.4146*	0.0954
VARRES	0.2106*	-0.4018*	-0.4018*	0.1501*	-0.4670*	0.2188*	0.3311*	-0.2887*		0.3396*	-0.081	-0.1945*	-0.3753*	-0.1422	0.4094*	0.2152*	0.3393*	0.0222
LAG	0.1764*	-0.1524*	-0.1524*	0.1169*	-0.0572*	-0.0699*	0.0880*	-0.0622*	0.0675*		-0.1043	-0.0239	-0.4406*	-0.1062	0.3031*	0.0544	0.2302*	-0.0366
BIGN	0.0062	0.1515*	0.1515*	-0.0322	0.0136	-0.0219	-0.0654*	-0.0154	-0.0404*	-0.0659*		0.1514	-0.0592	0.2232*	-0.0017	0.1756*	0.1246	0.0202
EXCH	-0.1543*	0.1822*	0.1822*	-0.1049*	0.1317*	0.0135	-0.1106*	0.1215*	-0.1822*	-0.1478*	0.0576*		-0.0088	0.2183*	-0.1191	0.1406	0.0792	-0.0551
BRLAG														0.0953	-0.5743*	-0.3569*	-0.5705*	0.0818
AIS	-0.0376*	0.1473*	0.1473*	-0.0499*	-0.0053	0.0273	-0.0146	-0.0088	-0.0408*	-0.0934*	0.1781*	0.0727*			-0.1164	-0.0262	-0.0975	.
CRL	0.2700*	-0.5183*	-0.5183*	0.3204*	-0.3149*	0.1437*	0.3799*	-0.0803*	0.5226*	0.2377*	-0.1129*	-0.1662*		-0.0857*		0.2902*	0.7612*	-0.0747
D_ CRΔ	0.1428*	-0.018	-0.018	-0.0237	-0.1894*	0.0068	0.0829*	-0.1171*	0.2074*	0.0927*	-0.0453*	-0.0966*		-0.0053	0.1807*		.	
DWN	0.1987*	-0.0299	-0.0299	-0.0314	-0.2888*	0.0066	0.0749*	-0.2498*	0.2541*	0.0932*	-0.0238	-0.1301*		-0.0055	0.1931*			-0.122
UP	-0.0453*	0.0279	0.0279	0.0026	0.1410*	-0.0138	0.0127	0.1477*	-0.0549*	0.0005	-0.0173	0.0437*		-0.0167	0.0003	-0.1882*		

The white area represents the correlations in the non-bankrupt sample and the grey shaded area shows the correlations in the bankrupt sample.

Table 7: Logistic Regression Results for the Complete Sample

	Dependent variable: ERROR			
	(1)	(2)	(3)	(4)
VARIABLES	Type I	Type II	Type I	Type II
lnAT	-0.285***	0.399***	-0.262***	0.489***
	(0.000)	(0.000)	(0.000)	(0.000)
BIGN	0.079	-0.715*	0.071	-0.676
	(0.353)	(0.080)	(0.403)	(0.106)
EXCH	-0.955***	-0.531	-0.960***	-0.440
	(0.000)	(0.242)	(0.000)	(0.342)
LAG	0.007***	0.004	0.007***	0.004
	(0.000)	(0.428)	(0.000)	(0.470)
ROA	-0.514***	-0.007	-0.524***	-0.010
	(0.000)	(0.949)	(0.000)	(0.927)
CURRENT	-0.186***	0.620***	-0.186***	0.633***
	(0.000)	(0.001)	(0.000)	(0.001)
PLOSS	0.742***	0.166	0.724***	0.083
	(0.000)	(0.600)	(0.000)	(0.792)
LEVG	0.642***	0.191	0.645***	0.256
	(0.000)	(0.701)	(0.000)	(0.596)
lnRET	-0.431***	0.553***	-0.426***	0.524***
	(0.000)	(0.001)	(0.000)	(0.002)
VARRES	71.099***	-74.620**	71.431***	-73.062**
	(0.000)	(0.041)	(0.000)	(0.046)
BRLAG		0.011***		0.011***
		(0.000)		(0.000)
D_JUNK			-0.125	-0.688**
			(0.469)	(0.034)
D_INV				0.281
				(0.779)
Constant	-1.202***	-3.544**	-1.256***	-3.787**
	(0.000)	(0.042)	(0.000)	(0.032)
Observations	21,572	465	20,865	465
Pseudo R2	0.305	0.334	0.298	0.341

Pval based on robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

For variable definitions please see the Appendix

Table 8: Logistic regression Results for Credit Rating Changes

	Dependent variable: ERROR					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Type I	Type II	Type I	Type II	Type I	Type II
lnAT	-0.397***	0.544	-0.192*	0.618**	-0.249**	0.585**
	(0.002)	(0.103)	(0.084)	(0.038)	(0.030)	(0.037)
BIGN	0.447	0.061	0.552	-0.251	0.558	-0.318
	(0.384)	(0.977)	(0.482)	(0.896)	(0.491)	(0.860)
EXCH	-0.753**	-0.952	-0.456	-1.296	-0.471	-1.245
	(0.044)	(0.364)	(0.214)	(0.181)	(0.207)	(0.240)
LAG	0.010***	-0.000	0.007***	0.020	0.007***	0.022
	(0.000)	(0.994)	(0.001)	(0.117)	(0.002)	(0.101)
ROA	-0.265	2.181	-0.303	3.124	-0.343	3.043
	(0.249)	(0.147)	(0.216)	(0.196)	(0.165)	(0.216)
CURRENT	-1.419***	0.473	-1.081***	0.512	-1.144***	0.515
	(0.000)	(0.254)	(0.000)	(0.291)	(0.000)	(0.265)
PLOSS	0.487**	-0.399	0.012	0.360	0.065	0.428
	(0.038)	(0.581)	(0.966)	(0.622)	(0.809)	(0.571)
LEVG	-1.478**	-0.445	-0.833	0.018	-0.887	-0.030
	(0.047)	(0.707)	(0.196)	(0.992)	(0.190)	(0.988)
lnRET	-0.717***	0.576	-0.351*	0.534	-0.391**	0.552
	(0.000)	(0.222)	(0.055)	(0.380)	(0.036)	(0.381)
VARRES	158.275***	-149.676	66.588	-133.081	68.943	-138.458
	(0.000)	(0.213)	(0.121)	(0.335)	(0.106)	(0.260)
BRLAG		0.018***		0.025***		0.025***
		(0.000)		(0.000)		(0.000)
D_CRΔ	0.759***	-1.100				
	(0.002)	(0.205)				
CRL			1.158***	-1.433***	1.061***	-1.406**
			(0.000)	(0.004)	(0.000)	(0.024)
D_DWN			0.818***	-0.479		
			(0.005)	(0.529)		
D_UP			-0.158			
			(0.801)			
DWN					0.150*	-0.046
					(0.053)	(0.879)
UP					0.079	
					(0.629)	
Constant	0.488	-0.876	-8.628***	7.057	-7.254***	6.716
	(0.731)	(0.840)	(0.000)	(0.519)	(0.000)	(0.585)
Observations	3,421	134	3,421	133	3,421	133
Pseudo R2	0.348	0.563	0.498	0.646	0.494	0.644

Pval based on robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
For variable definitions please see the Appendix

Table 9: Logistic Regression Results for Credit Rating Severity and Timing

	Dependent variable: ERROR					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Type I	Type II	Type I	Type II	Type I	Type II
lnAT	-0.204*	0.528*	-0.201*	0.569*	-0.207*	0.750**
	(0.070)	(0.094)	(0.080)	(0.057)	(0.074)	(0.020)
BIGN	0.538	1.787	0.394	-0.379	0.408	0.625
	(0.498)	(0.311)	(0.644)	(0.830)	(0.620)	(0.811)
EXCH	-0.448	-1.381	-0.541	-1.292	-0.538	-1.934
	(0.218)	(0.200)	(0.145)	(0.194)	(0.137)	(0.113)
LAG	0.007***	0.023	0.007***	0.022	0.007***	0.026*
	(0.002)	(0.192)	(0.005)	(0.120)	(0.005)	(0.055)
ROA	-0.305	1.823	-0.292	3.034	-0.298	2.907
	(0.235)	(0.379)	(0.254)	(0.191)	(0.244)	(0.255)
CURRENT	-1.086***	0.053	-1.144***	0.537	-1.151***	0.668
	(0.000)	(0.920)	(0.000)	(0.265)	(0.000)	(0.222)
PLOSS	0.031	-0.800	-0.025	0.478	0.001	-0.045
	(0.908)	(0.321)	(0.926)	(0.503)	(0.998)	(0.963)
LEVG	-0.862	0.459	-0.747	-0.059	-0.713	-0.154
	(0.177)	(0.835)	(0.259)	(0.975)	(0.284)	(0.931)
lnRET	-0.343*	1.241*	-0.348*	0.579	-0.311*	0.641
	(0.061)	(0.066)	(0.061)	(0.360)	(0.095)	(0.335)
VARRES	66.255	-208.018	58.299	-132.919	63.897	-200.970
	(0.124)	(0.188)	(0.181)	(0.313)	(0.134)	(0.215)
BRLAG		0.027***		0.025***		0.027***
		(0.000)		(0.000)		(0.000)
CRL	1.127***	-1.131***	1.159***	-1.482***	1.162***	-1.357***
	(0.000)	(0.009)	(0.000)	(0.002)	(0.000)	(0.002)
D_1NOTCH	0.569	-1.415				
	(0.106)	(0.330)				
D_2NOTCH	0.972**	1.749				
	(0.023)	(0.124)				
D_3NOTCH	0.991**	-2.296*				
	(0.010)	(0.072)				
NRQ			0.450***	0.024		
			(0.009)	(0.961)		
D_FQ1					0.211	1.022
					(0.595)	(0.272)
D_FQ2					0.076	-0.140
					(0.849)	(0.905)
D_FQ3					0.705*	-0.873
					(0.074)	(0.302)
D_FQ4					0.852***	-1.236
					(0.010)	(0.192)
Constant	-8.308***	5.999	-8.216***	7.198	-8.250***	5.238
	(0.000)	(0.465)	(0.000)	(0.518)	(0.000)	(0.403)
Observations	3,421	134	3,404	133	3,404	133
	0.499	0.701	0.500	0.647	0.504	0.665

Pval based on robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
For variable definitions please see the Appendix

Table 10: Logistic Regression Results for Clearly Non-Specialized Auditor Interactions

	Dependent variable: ERROR					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Type I	Type II	Type I	Type II	Type I	Type II
lnAT	-0.172	0.544	-0.240	0.557	-0.132	0.454
	(0.260)	(0.311)	(0.128)	(0.393)	(0.372)	(0.429)
BIGN	0.381		0.352		0.173	
	(0.628)		(0.664)		(0.834)	
EXCH	-0.560	-0.773	-0.547	-0.738	-0.673	-0.635
	(0.193)	(0.438)	(0.223)	(0.448)	(0.119)	(0.535)
LAG	0.008***	-0.004	0.007***	-0.007	0.007***	-0.003
	(0.001)	(0.783)	(0.002)	(0.702)	(0.003)	(0.869)
ROA	-0.216	4.044**	-0.270	3.584*	-0.180	4.056**
	(0.425)	(0.028)	(0.308)	(0.056)	(0.562)	(0.024)
CURRENT	-0.970***	0.965	-1.013***	0.837	-0.988***	0.897
	(0.001)	(0.148)	(0.001)	(0.214)	(0.001)	(0.194)
PLOSS	0.362	-0.525	0.433	-0.633	0.385	-0.449
	(0.259)	(0.521)	(0.181)	(0.422)	(0.218)	(0.567)
LEVG	-0.434	5.189***	-0.454	4.568**	-0.267	5.070***
	(0.517)	(0.007)	(0.548)	(0.038)	(0.726)	(0.008)
lnRET	-0.272	0.324	-0.335*	0.184	-0.254	0.182
	(0.171)	(0.590)	(0.091)	(0.787)	(0.203)	(0.777)
VARRES	-18.279	-84.188	-15.028	-24.049	-16.500	-73.888
	(0.687)	(0.659)	(0.766)	(0.896)	(0.744)	(0.672)
CNSA5	-1.470	17.179***	-0.261	18.815***	-0.382	18.945***
	(0.210)	(0.000)	(0.670)	(0.000)	(0.622)	(0.000)
BRLAG		0.021***		0.023***		0.023***
		(0.003)		(0.006)		(0.003)
CRL	1.165***	-1.339*	1.043***	-1.159	1.204***	-1.358**
	(0.000)	(0.053)	(0.000)	(0.105)	(0.000)	(0.043)
D_UP	-0.363					
	(0.698)					
D_DWN	0.954**	-0.286				
	(0.011)	(0.842)				
D_DWN x CNSA5	1.576	-14.291***				
	(0.221)	(0.000)				
UP			0.140			
			(0.432)			
DWN			0.179*	-0.246		
			(0.055)	(0.568)		
DWN x CNSA5			0.012	-14.387***		
			(0.943)	(0.000)		
NRQ					0.621***	-0.315
					(0.003)	(0.641)
NRQ x CNSA5					0.074	-15.471***
					(0.824)	(0.000)
Constant	-9.359***	-1.548	-7.803***	-2.649	-9.592***	-1.306
	(0.000)	(0.846)	(0.000)	(0.747)	(0.000)	(0.859)
Observations	2,691	79	2,691	79	2,678	78
Pseudo R2	0.490	0.611	0.479	0.634	0.496	0.619

Pval based on robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
For variable definitions please see the Appendix