# Qualitative Corporate Disclosure and Credit Analysts' Soft Rating Adjustments

Zahn Bozanic

The Ohio State University

Pepa Kraft*

New York University

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### Abstract

Credit ratings are determined by both quantitative and qualitative inputs. While academics have extensively studied quantitative models of credit risk analysis, far less is known about *qualitative* adjustments to credit analysts' models' outputs ("soft adjustments"). We examine whether and how credit analysts employ borrowers' credit risk relevant qualitative disclosure in making their credit risk assessments. We provide evidence which suggests that credit analysts impound the information conveyed by borrowers' qualitative disclosure in their credit ratings. Our results further indicate that the "soft", but not "hard", adjustments are the mechanism by which the information in borrowers' qualitative disclosure is impounded into the publicly reported rating. We next examine whether the efforts analysts expend to extract credit risk relevant information from qualitative disclosure affects the informativeness of credit ratings. We find that credit rating downgrades that involve soft adjustments or greater amounts of qualitative disclosure are more informative than those that do not; however, the increase in informativeness diminishes after the repeal of the Regulation Fair Disclosure exemption for credit rating agencies.

# 1 Introduction

We examine the role qualitative disclosure plays in credit risk analysis. The lack of research on the use of qualitative disclosure by credit analysts is puzzling considering that credit analysts are major users of corporate disclosures whose ratings have significant implications for firms' access to and cost of capital. Prior research on credit analysts focuses on their reliance on quantitative modeling to produce initial credit ratings. In such models, the traditional Altman (1968) financial statement variables appear amongst other determinants of credit quality. More recently, research has extended the purview of how credit rating analysts arrive at their credit risk assessments by examining analysts' soft adjustments, that is, qualitative adjustments made to the rating recommendations produced by their quantitative models (Kraft (2014)). While researchers can reproduce the quantitative models credit analysts rely on to make their initial credit assessments, the inputs analysts rely on in making their soft rating assessments are less understood. In this study, we investigate the qualitative inputs that may influence credit rating analysts' soft rating assessments as well as the informativeness of those assessments.

According to the credit rating agencies, credit analysts consider several factors in making their soft adjustments, such as caliber of management, financial transparency, and competitiveness (Standard & Poor's (2008); Moody's (2007)). We focus on a single channel by which credit rating analysts inform their soft adjustments, qualitative disclosure, for at least two reasons. First, beyond the traditional quantitative inputs of credit analysts' models from financial statements, how managers contextualize the quantitative information in the financial statements is a likely complementary information channel. A large, recent body of research on the informativeness of qualitative disclosure (for example, Li (2008); Davis et al. (2012); etc.) lends credibility to the conjecture that stakeholders beyond equity market investors and equity analysts plausibly use this form of information.

Second, prior to the passing of Regulation Fair Disclosure ("Reg FD") in 2000, equity and credit analysts operated under a level playing field in that both had direct access to management and the attendant private information conveyed by managers. However, post-

Reg FD, the level playing field was tilted by disallowing equity analysts' access to managers, yet the access remained for credit analysts. Given the lack of timeliness and inaccuracy of ratings prior to the credit crisis as a result of the close relationship between credit analysts and management, this relationship was questioned and the Dodd-Frank Wall Street Reform and Consumer Protection Act ("the Dodd-Frank Act") repealed the exemption Reg FD granted to credit analysts in 2010. Hence, credit analysts' information supply diminished, arguably increasing the search costs of information acquisition and the processing costs once found. As a result, credit analysts are likely to spend more time and effort examining firm disclosures for information that cannot be captured by their quantitative models alone.

We examine several plausible, credit risk relevant proxies for the qualitative information found in borrowers' annual reports. We first examine the extent of information on debt-related topics in the disclosure, such as liquidity, solvency, and covenants. Second, we examine the extent of earnings-related topics, given that credit analysts are likely to scrutinize earnings disclosures since such disclosures may signal the firm's ability to service debt, especially during loss periods (e.g., Pownall et al. (1993); Skinner (1994); Easton et al. (2009)). Third, credit analysts are likely interested in managerial outlooks in addition to historical trends when forming ratings change and outlook decisions, whether in the form upgrades, downgrades, or additions to watch lists. We therefore examine the provision for forward-looking disclosure (Li (2010a)). Fourth, some qualitative disclosure may not explicitly mention debt or earnings topics or provide forward-looking disclosures; however, the disclosure may more generally convey uncertainty. While uncertainty is a concern for both equity and credit analysts, equity investors are likely to be relatively more uncertainty-seeking for known risks than debt investors. Hence, we examine how firm disclosures reflect uncertainty (Loughran and McDonald (2011)). Fifth, analysts are likely to be concerned with the managerial assessments of firms' competitive environments, which we capture from a disclosure perspective using the approach found in Li et al. (2013). If management is overly concerned with its competition, the disclosure of those concerns could portend declining market share and thus debt service concerns. Finally, following prior literature that has examined the optimism conveyed by disclosure, we examine how disclosure tone influences credit analysts' beliefs (Loughran and

McDonald (2011)).

We first investigate whether publicly-reported credit ratings reflect the information conveyed by qualitative disclosure. This step allows us to assess the information content of qualitative disclosure by examining a standard credit rating agency output, the rating publicly issued by the rater, which is the traditional metric consumed by investors as well as studied by academics. We find in levels analysis that ratings tend to be lower when firms provide more disclosure on debt-related topics and higher when firms provide more disclosure on earnings-related topics. These results are consistent with managers of firms disclosing debt-related topics that appear to reflect adverse credit conditions and earning-related topics that reflect favorable information for debt investors. We also find some evidence that ratings tend to be lower when firms provide more forward-looking disclosure. We then attempt to more directly identify the relation between reported ratings and qualitative disclosure by examining disclosure changes. We find that increases in debt-related disclosure are associated with lower reported ratings and some evidence with respect to increases in forward-looking disclosure. In contrast to the levels analysis, we find strong evidence that increases in both competition-related disclosure and disclosure tone are associated with higher reported ratings. While the result related to disclosure tone is as expected, the results with respect to competition is contrary to our expectation.

Although these results shed light on whether qualitative information is reflected in reported credit ratings, they do not speak to the mechanism through which the information flows, that is, whether the information conveyed by qualitative disclosure merely reflects that contained in credit analysts' quantitative models or whether the information is uniquely impounded into their soft adjustments. Therefore, to answer our primary research question, we next investigate whether credit rating analysts employ credit risk relevant information conveyed by qualitative disclosure in making both their soft and hard adjustments, respectively.

We find that credit rating analysts are more likely to make credit risk *increasing* soft adjustments when firms provide more disclosure on debt-related topics. When managers provide more discussion on earnings-related topics, credit rating analysts are more likely to make credit risk *decreasing* soft adjustments. We also find that forward-looking disclosure increases the likelihood that credit rating analysts make credit risk *increasing* soft adjustments. In examining disclosure changes, we find that increases in debt-related disclosure are associated with a higher likelihood of credit risk *increasing* soft adjustments and some evidence that changes in forward-looking disclosure do as well. Similar to the results for reported ratings, we find strong evidence that increases in both competition-related disclosure and disclosure tone are associated with a higher likelihood of credit risk *decreasing* soft adjustments.

While the results on the relation between credit rating analysts' soft adjustments and qualitative disclosure largely mirror those related to the reported rating, the economic significance of the impact of qualitative disclosure on soft adjustments is generally greater. Importantly, the results hold after controlling for an extensive set of variables, such as size, leverage, profitability, cash flow, tangibility, scale of diversification, corporate governance, industry concentration, return volatility, and financial reporting quality. In stark contrast, we do not find that any of our proxies for qualitative disclosure are related to hard rating adjustments, i.e., those arising strictly from analysts' adjustments to the data underlying their quantitative modeling. Taken together, the results suggest that qualitative disclosure is useful to credit rating analysts when making their risk assessments and soft adjustments are the conduit through which qualitative information is impounded into the actual, publicly-reported credit rating.

Next, we examine whether the repeal of credit analysts' Reg FD exemption incentivized analysts to cultivate additional information within firms' public disclosures since their private access to management was curtailed. Ceteris paribus, if analysts do spend more time and effort examining firm disclosures for information not captured by their quantitative models, we would expect the relation between qualitative disclosure and soft adjustments to strengthen. However, if the costs of the repeal are too great for analysts to modify their acquisition and processing behaviors, we may observe no change in the strength of the relation. We find some evidence that credit analysts appear to rely more on changes in earnings, forward-looking, and uncertainty-related disclosure after the repeal of the Reg FD exemption.

Lastly, while we have established that credit rating analysts appear to use information from qualitative disclosure to make their soft ratings adjustments, it is unclear if the efforts expended both before and after the repeal of the Reg FD exemption affect the informativeness of the rating. We therefore examine the relative informativeness of credit rating changes involving soft adjustments and greater amounts of qualitative disclosure. Consistent with prior research (Holthausen and Leftwich (1986); Jorion et al. (2005)) we assess rating informativeness by the price response to rating changes. We find that credit rating downgrades that involve soft adjustments prior to the repeal of the Reg RD exemption are more informative than downgrades that do not. Further, the greater the level of credit risk relevant qualitative disclosure prior to the repeal, the more informative the downgrade. However, consistent with Dimitrov et al. (2014), the increase in informativeness for downgrades involving either soft adjustments or greater amounts of qualitative disclosure is diminished after the repeal.

Our paper makes several contributions to the literatures on information intermediaries and corporate disclosure. First, by providing insights on how credit analysts employ credit risk relevant qualitative information in generating their primary output, credit ratings, we contribute to the literature on information intermediaries. Critically, instead of merely linking qualitative information to the actual, publicly-reported rating, which relies on both quantitative and qualitative assessments, we are able to link qualitative information to the soft adjustments themselves, i.e., precisely where the qualitative information is likely to have the largest impact. Second, we contribute to the growing literature on qualitative disclosure which has largely focused on how investors and equity analysts consume and utilize qualitative information found in corporate disclosures. We extend this line of research to demonstrate the role qualitative information plays in credit markets. Our findings should be of interest to academics in devising their credit risk models, regulators in creating new standards that may cater to debt clienteles, and managers of firms in choosing how best to convey risk relevant information to influence the beliefs of credit analysts.

The paper proceeds as follows. Section 2 provides institutional background on the credit rating process and develops our hypotheses. Section 3 discusses the data used in the empirical analysis as well as descriptive statistics. Section 4 outlines the empirical methodology and presents our results. Section 5 concludes.

# 2 Hypothesis Development

## 2.1 The Role of Soft Information in the Credit Rating Process

A major task of credit rating agencies is to collect and process information about borrowers and convert this information into ratings that can be communicated easily. Hard information, such as financial ratios based on accounting numbers, can easily be collected, stored, transmitted, and verified by other parties. However, despite the fact that variation in accounting numbers explains a large proportion of ratings, it does not fully explain the underlying ratings process. Some of the information relevant to the lending and rating process is qualitative or soft, such as disclosure narratives, and its credit relevance requires a judgment call by loan officers and credit analysts (Dietrich and Kaplan (1982); Stein (2002); Campbell and Loumioti (2013)). While much of this information is unstructured, once it is reduced to a series of numbers, it can be classified as hard information for modeling purposes (Petersen (2004)).

A substantial literature on bankruptcy and credit risk prediction uses hard accounting and stock price data (Horrigan (1966); West (1970); Pogue and Soldofsky (1969); Kaplan and Urwitz (1979); Blume et al. (1998)), yet corporate disclosures contain a large amount of unstructured narrative information, such as the notes to the financial statements in firms' 10-K filings. Qualitative, or narrative, disclosures are a rich information source as they contain information about the underlying data generating functions, such as firms' accounting policies and reporting incentives (Li (2010b)). A growing body of literature on qualitative disclosure finds that such disclosure conveys information content with respect to both firm fundamentals and stock price reactions that is incremental to standard quantitative measures of information content (Tetlock et al. (2008); Engelberg (2008); Li (2008); Davis et al. (2012); Bozanic and Thevenot (2014)). Further, given the evidence from existing research that qualitative disclosures incrementally predict future performance (Li (2008); Li (2010a)), it is likely that qualitative disclosures contain incremental information content that predicts credit risk. Therefore, our initial conjecture is that rating analysts impound the information contained in qualitative disclosure into their ratings. Since some may contend that qualitative disclosures may reflect generic "boilerplate," a test of our conjecture allows us to rule out this possibility.

However, such a test does not provide us with an understanding of the mechanism by which credit analysts impound qualitative disclosure into their reported ratings, that is, whether qualitative disclosure influences analysts' hard, or quantitative, adjustments versus their soft, or qualitative, adjustments, which is our primary research question.

Standard & Poor's performs "quantitative, qualitative, and legal analyses" in forming a rating opinion (Standard & Poor's 2008, p.4). Standard & Poor's supplements the financial statement analysis with quantitative and qualitative considerations. Hard or quantitative adjustments include adjustments to financial statements. Soft or qualitative considerations include assessments of the caliber of management, financial transparency, and a company's competitiveness (Standard & Poor's 2008, p.4, 22). Standard & Poor's claims that the extent of information risk influences the level of the rating, and in cases of extreme information risk, whether a rating is assigned (Standard & Poor's 2008, p.40). Moody's rating process is similar in that it includes both quantitative and qualitative aspects. In addition to its hard adjustments, Moody's examines the following qualitative factors for its soft adjustments: industry structure, financial policy, management quality, contingent liabilities, aggressive accounting, weak accounting controls, governance risk, and event risk (Moody's 2007, slide 43).

Appendix A provides an illustration of a typical Moody's rating process for Kraft Foods Group. Moody's rating analysts assign each industry group a weighted rating grid that consists of primarily quantitative factors. The rating grid captures assessments of a firm's competitive position, size, stability, profitability, leverage, and financial strength. The rating grid first produces an indicated rating based on reported financial data ('as reported') before producing an updated indicated rating based on adjustments to the reported data ('as adjusted'). Kraft Foods Group's adjusted financials indicate that leverage is higher than that inferred from its reported financials. The Debt/EBITDA ratio calculated using adjusted financials is substantially greater and the EBIT/interest expense ratio is substantially lower than those calculated using reported financials. As a result of the adjustments, Kraft Foods Group's indicated rating based on 'as adjusted' ratios (Baa1) is one notch lower than the rating based on 'as reported' financials (A3), denoted by HARD = +1. Kraft (2014) shows that the major hard adjustment includes off-balance-sheet debt, leading to substantially higher leverage ratios. Soft adjustments, denoted by SOFT = +1, lower the rating by another notch to Baa2. While the grid provides guidance on what prompted the hard adjustment, little information is given on the underlying rationale for a given soft adjustment.

To the extent our proxies for qualitative disclosure reflect the information credit analysts take into consideration when making their soft adjustments, our next conjecture is that credit analysts impound the information contained in qualitative disclosure into their soft rating adjustments. If we find that our proxies for qualitative disclosure are related to soft adjustments but are unrelated to hard adjustments, the latter test will corroborate the findings of the former test by ruling out the possibility that the risk-relevant information conveyed by soft disclosure merely reflects analysts' adjusted model inputs.

## 2.2 The Impact of the Repeal of Reg FD

On October 23, 2000, the Securities and Exchange Commission (SEC) implemented Regulation Fair Disclosure ("Reg FD"). Reg FD was adopted to prevent selective disclosure to those who would be reasonably expected to trade securities on the basis of the information or provide others with advice about securities trading (Ohlson et al. (2010)). Since Reg FD targeted firms' selective disclosure to equity analysts, an exemption was granted to rating agencies. That is, Reg FD does not apply to disclosures made to rating agencies provided that the ratings are made publicly available (Carbone (2010)). However, on September 29, 2010, the SEC amended Reg FD to remove the express exemption for disclosures of material non-public information for credit rating agencies (former Rule 100(b)(2)(iii) of Regulation FD). This was required by Section 939B of the Dodd-Frank Wall Street Reform and Consumer Protection Act ("the Dodd-Frank Act") and became effective on October 4, 2010 (Ohlson et al. (2010)).

Given that credit analysts' private access to management was curtailed after the repeal of the exemption, we examine whether the repeal increased analysts' incentives to cultivate qualitative information from firms' public disclosures. If analysts spend more time and effort acquiring and processing firm disclosures for information not captured by their quantitative models, we would expect the relation between qualitative disclosure and soft adjustments to strengthen after the repeal of the Reg FD exemption. However, if it is overly costly for analysts to modify their acquisition and processing behaviors, we may observe no change in the strength of the relation. Moreover, the credit rating agencies that have publicly addressed the removal of the exemption under Regulation FD do not believe that it will change the way issuers share material non-public information with the rating agencies (Carbone (2010)).

## 2.3 The Informativeness of Soft Adjustments

Analysts presumably expend effort in making their soft adjustments to assess credit risk from qualitative factors that cannot be captured by their quantitative modeling. As it would be relatively easy to generate a rating for a firm that provides tabular information alone, the efforts analysts expend in cultivating information from complex disclosures presumably increases the value of and demand for their services (Lehavy et al. (2011)). Given the processing costs involved in extracting credit risk relevant qualitative information from disclosure (Miller (2012); Loughran and McDonald (2014)), ratings that incorporate soft adjustments may be more informative. We use standard event study methodology (Holthausen and Leftwich (1986); Hand et al. (1992); Jorion et al. (2005)) to assess the price impact of rating changes that incorporate soft adjustments.

For our last set of tests, we compare the equity market reaction to rating changes that involve soft rating adjustments and greater levels of qualitative disclosure before and after the repeal of the Reg FD exemption. Since credit analysts' private information supply diminished, even if analysts spend more time and effort examining firms' public disclosures for qualitative information, credit rating informativeness may at best remain unchanged. Further, while ratings became more informative after the implementation of Reg FD due to the exemption granted to credit rating agencies (Jorion et al. (2005)), after the repeal of the exemption, downgrades became less informative (Dimitrov et al. (2014)). As a consequence, the relative informativeness of credit rating changes that involve soft rating adjustments and greater levels of qualitative disclosure after the repeal is ultimately an empirical question for which we form no prediction.

# 3 Data and descriptive statistics

## 3.1 Sample

We derive our sample of soft and hard rating agency adjustments from Moody's Financial Metrics. We retrieve all industry methodology reports for the period 2002 through 2013. Our sample commences with 2002 because it is the first year in which we have data from Moody's Financial Metrics. We derive our sample of annual reports from the Securities and Exchange Commission's EDGAR database. We retrieve all Form 10-K filings for the same period corresponding to the availability of the Moody's Financial Metrics data. To merge the samples, we first match the firms from Moody's Financial Metrics to Compustat GVKEY and CIK firm identifiers. We then match the CIK code on Form 10-K filings to the Compustat GVKEY. We obtain all credit rating change announcements during the sample period from RatingsXpress. We collect all announcements of long-term entity ratings by Standard & Poor's (issuer ratings). Rating levels are numerical transformations of the alphanumerical rating codes from 1 to 21 (AAA to C). Stock prices are obtained from CRSP and are used to calculate cumulative abnormal returns surrounding announcements of rating changes.

Rating agency adjustments are calculated using the Moody's Financial Methodology reports. Hard rating agency adjustments (HARD) are calculated as the difference between the rating produced from an unadjusted quantitative model (RATE_IND_REP) and a hypothetical rating based on a model using adjusted financial statements (RATE_IND_ADJ). Greater values of HARD imply greater credit risk assessment arising from hard or quantitative factors. Soft rating agency adjustments (SOFT) are calculated as the difference between the actual reported rating (RATE) and a hypothetical rating based on a model using adjusted financial statements (RATE_IND_ADJ). Greater values of SOFT imply greater credit risk assessments arising from soft or qualitative factors. Rating changes (RATE_CHANGE) are calculated as the difference between the numerical values assigned to the 21 rating codes. A downgrade from AAA to AA+ results in a numerical value of 1. Thus, greater values imply increases in assessed credit risk. Cumulative abnormal return (CAR) is calculated as the cumulative stock return over the three day window (-1,+1) around the rating change less the corresponding return on the CRSP value-weighted index.

Our textual proxies for qualitative disclosure found in annual reports are intended to capture managerial narrative that conveys information related to credit risk. Following prior literature, we use textual analysis to extract firm-specific measures of managers' perceptions of risk-relevant topics likely to be of interest to credit analysts. That is, from firms' 10-K's, we extract proxies of qualitative disclosure related to debt, profitability, competitiveness, managerial optimism, managerial outlooks, and managerial perceptions of uncertainty. While the first four are likely to be related to current risks, the latter two are likely to be related to assessments of future risks.

First, we measure qualitative disclosure related to debt (DEBT) using the number of references to a debt-related topic in a firm's 10-K scaled by 10-K total word count. Second, we measure qualitative disclosure related to earnings (EARNINGS) using the number of references to an earnings-related topic in a firm's 10-K scaled by 10-K total word count. Third, we measure qualitative disclosure related to prospective disclosure (FLS) using the number of forward-looking statements in a firm's 10-K scaled by 10-K total sentence count. If a sentence contains at least one forward-looking term, it is considered to be a forward-looking statement (Li (2010a)). Fourth, we measure qualitative disclosure related to uncertainty (UNCERT) using the number of uncertainty-related words in a firm's 10-K scaled by 10-K total word count (Loughran and McDonald (2011)). Fifth, we measure managerial perception of competitiveness (COMP) using the number references to competition in firm's 10-K scaled by 10-K total word count (Li et al. (2013); Bushman et al. (2014)). Finally, we measure disclosure tone using the number of optimistic less pessimistic words in a firm's 10-K scaled by 10-K total word count (Loughran and McDonald (2011)). See Appendix B for further detail regarding the words lists used to generate the measures.

We include a number of control variables. Size (SIZE) is measured by the logarithm of total assets. Leverage (LEV) is measured as the sum of short-term debt and long-term debt divided by total assets. Market-book-ratio (MB) is calculated as market value of equity divided by book value of shareholders' equity. Profitability (ROA) is measured as the ratio of operating income to total assets. Cash flow liquidity (CFO) is measured as the ratio of operating cash flow to the sum of short-term and long-term debt. Tangibility (TANG) is measured as the ratio of the sum of inventory and property, plant, and equipment to total assets. LOSS is a dummy variable equal to one if net income before extraordinary items is negative, and zero otherwise. Business segments (BSEG) is the number of business segments and geographic segments (GSEG) is the number of geographic segments. Institutional ownership (IO) is the number of shares held by institutional investors at the end of the quarter and then averaged within the year. The Herfindahl index (HHI) is a measure of industry concentration based on market share. Firm maturity (MAT) is defined as the number of years a firm has appeared on Compustat. Return volatility (RETVOL) is stock return volatility calculated as the standard deviation of daily stock returns. To measure financial statement quality, we use the FSD Score (FSD) which is based on the level of financial statement divergence from Benford's Law following Amiram et al. (2014) where greater value implies lower financial statement quality. See Appendix C for a complete list of variable definitions.

To conduct our analyses, we require that firms have sufficient data to calculate rating agency adjustments and sufficient financial data to calculate firm-level control variables. The final sample is 2,526 firm-years representing 732 firms. Variables are winsorized at the 0.5% and 99.5% level. With respect to the analysis on rating informativeness, we eliminate firms with extreme rating changes, i.e., firms with rating changes greater than 6 or less than 6 notches.

## 3.2 Descriptive Statistics

Table 1, Panel A presents descriptive statistics for the sample used in our initial analysis on soft rating adjustments and qualitative disclosure. Table 1, Panel B presents descriptive statistics for the sample used in our secondary analysis on the informativeness of credit ratings changes, which we discuss in detail in Section 4.3. The average value of SOFT is 0.56, which implies that on average, credit analysts lower the rating by approximately half a notch due to qualitative risk factors. In contrast, the average value of HARD is 0.29, which implies that on average, credit analysts lower the rating by approximately quarter of a notch due to quantitative risk factors. The average value of RATE is 11 which corresponds to a BB+ (or

Ba1) rating.

In terms of the qualitative disclosure proxies, on average, 1.3% of a firms' 10-K disclosures discuss debt-related topics, 0.5% discuss earnings-related topics, 1.3% discuss uncertainty-related topics, and 0.1% discuss competition-related topics. Of the statements firms make in their 10-K's, roughly one quarter can be considered as forward-looking. 0.1% of the average firm's 10-K narrative disclosure contains references to competition and -0.9% reflects pessimistic tone on net. The average 10-K filing has roughly 70,000 words and 2,200 sentences (untabulated).

Regarding the controls for firm characteristics that are likely factors analysts use in making their hard adjustments, the average firm has assets of 14.2 billion, leverage of 0.34, return on assets of 0.09, and market-to-book ratio is 3.3. Cash flow from operations (scaled by total debt) is 0.49, the fraction of tangible assets is 0.46, and 18% firm-years have negative net income. In terms of the controls that are likely factors analysts use in making their soft adjustments, the average firm has 6.4 business segments, 7.6 geographic segments, institutional holdings of 213 million shares, a Herfindahl index of 0.30, and stock return volatility is 0.03. Lastly, the measure of financial reporting quality based on Benford's Law is 0.03, which is consistent with the results in Amiram et al. (2014).

Table 2 presents the Pearson correlations of SOFT with the proxies for qualitative disclosure and firm characteristic variables. SOFT has significant negative associations with EARNINGS and significant positive associations with FLS and UNCERT. This implies that references to forward-looking statements and uncertainty-related disclosure are correlated with worse (i.e., credit risk increasing) SOFT adjustments whereas references to earnings-related disclosure are correlated with better (i.e., credit risk decreasing) SOFT adjustments.

# 4 Methodology and Empirical Results

## 4.1 Reported Ratings

As a preliminary test of whether our proxies for qualitative disclosure are likely to contain any risk-relevant information for credit analysts, we initially examine their relation to the ratings the agency publicly reports (RATE). This is a critical first step towards understanding the mechanism by which the information contained in qualitative disclosure is impounded into the actual rating. In that sense, this test in part validates our qualitative disclosure proxies before isolating the possible mechanism, i.e., soft versus hard adjustments, by which the information flows into the actual rating. We estimate a regression of the following form:

$$\begin{aligned} RATE_{i,t+1} &= \alpha + \beta_1 DEBT_{i,t} + \beta_2 EARNINGS_{i,t} + \beta_3 FLS_{i,t} \\ &+ \beta_4 UNCERT_{i,t} + \beta_5 COMP_{i,t} + \beta_6 TONE_{i,t} \\ &+ \beta_7 RATE\_IND\_REP_{i,t} + \sum \beta_j HARD\_FIRM\_Controls_{i,t} \\ &+ \sum \beta_k SOFT\_FIRM\_Controls_{i,t} + \epsilon \end{aligned} \tag{1}$$

We include three types of controls. First, we include RATE_IND_REP to control for the estimates produced by analysts' quantitative models prior to financial statement adjustments. Second, we include controls for firm characteristics that likely mirror the variables that serve as inputs to analysts' quantitative models and are the focus of their hard adjustments (HARD_FIRM_CONTROLS): SIZE, LEV, MB, ROA, CFO, TANG, and LOSS. Third, we include controls likely to capture firm complexity, monitoring, competition, asset volatility, and financial statement quality (SOFT_FIRM_CONTROLS): BSEG, GSEG, IO, MAT, HHI, RETVOL, and FSD. These variables represent the issues analysts consider when making their soft adjustments (Standard & Poor's (2008); Moody's (2007); Ashbaugh-Skaife et al. (2006)). Standard errors are clustered by firm and year fixed effects are included. Further, given the high collinearity between FLS and UNCERT, we include separate regressions that augment the baseline regression with specifications that exclude each proxy individually.

The results from estimating Equation 1 can be found in Table 3, Panel A. Column 1 includes both FLS and UNCERT, whereas Column 2 removes UNCERT and Column 3 removes FLS to address the collinearity issue. In all specifications, the full set of controls is included but the coefficients for the hard and soft firm controls are not reported for expositional economy. In Column 1, the coefficient on DEBT is 80.61 and the coefficient on EARNINGS is

-200.54; both coefficients are statistically significant at the 1% level or better. In terms of economic magnitudes, a one standard deviation increase in DEBT (EARNINGS) is associated with a 0.30 notch increase (0.32 notch decrease) in RATE, or 2.7% (2.9%) of the mean value of RATE. These results imply that actual ratings tend to be lower when firms provide more disclosure on debt-related topics and higher when firms provide more disclosure on earnings-related topics. When FLS and UNCERT are included in the same regression (Column 1), only FLS is statistically significant. When we exclude UNCERT (Column 2), FLS continues to load; however, when we exclude FLS (Column 3), UNCERT remains insignificant. In terms of economic magnitudes, a one standard deviation increase in FLS is associated with a 0.01 notch increase in RATE, or 0.1% of the mean value of RATE.

Taken together, we view these results as supporting the prediction that publicly-reported credit ratings reflect the information conveyed by qualitative disclosure incremental to the hard financial statement inputs of analysts' quantitative models as well as the soft factors that credit analysts are known to consider in making their soft adjustments. However, given the tests are of association, in Panel B of Table 3, we take efforts to more cleanly identify the link between qualitative disclosure and reported ratings by conducting a changes analysis to mitigate concerns that our textual proxies reflect general firm-level characteristics. In so doing, we find similar results for ΔDEBT yet, in contrast to the results found in Panel A, we find no empirical evidence for ΔEARNINGS and some evidence for ΔFLS in the absence of ΔUNCERT (Column 2). However, across all three specifications, we find consistent evidence for ΔCOMP and ΔTONE. In Column 1, the coefficient on ΔCOMP is -88.87 and the coefficient on ΔTONE is -14.54; with the coefficient on the former (latter) statistically significant at the 5% (1%) level or better. In terms of economic magnitudes, a one standard deviation increase in ΔCOMP (ΔTONE) is associated with a 0.03 (0.04) notch decrease in RATE, or 99.5% (151%) of the mean value of RATE.

## 4.2 Hard versus Soft Adjustments

### 4.2.1 Qualitative Disclosure and Soft Adjustments

Having established that qualitative disclosure appears to provide analysts with information that is impounded in their publicly reported ratings, we next turn to our primary research question: whether the information conveyed by qualitative disclosure merely reflects that contained in credit analysts' quantitative models or whether the information is uniquely impounded into their soft adjustments. In order to shed light on this question, we first modify Equation 1 as follows:

$$\begin{aligned} SOFT_{i,t+1} &= \alpha + \beta_1 DEBT_{i,t} + \beta_2 EARNINGS_{i,t} + \beta_3 FLS_{i,t} \\ &+ \beta_4 UNCERT_{i,t} + \beta_5 COMP_{i,t} + \beta_6 TONE_{i,t} \\ &+ \beta_7 RATE\_IND\_ADJ_{i,t} + \sum \beta_j HARD\_FIRM\_Controls_{i,t} \\ &+ \sum \beta_k SOFT\_FIRM\_Controls_{i,t} + \epsilon \end{aligned} \tag{2}$$

Aside from the change in dependent variable, Equation 2 is similar to Equation 1 with one important exception: in contrast to the indicated *reported* rating (RATE_IND_REP), we now control for the indicated *adjusted* rating (RATE_IND_ADJ), that is, the rating produced from credit analysts' models after the underlying financial statement data used to estimate the models have undergone hard, but not soft, adjustments.

The results from estimating Equation 2 can be found in Table 4, Panel A, which follows a similar format to that found in Table 3. We find in Column 1 that the coefficient on DEBT is 35.37 and the coefficient on EARNINGS is -190.59; both coefficients are statistically significant at the 1% level or better. In terms of economic magnitudes, a one standard deviation increase in DEBT (EARNINGS) is associated with a 0.13 notch increase (0.31 notch decrease) in SOFT, or 23% (54%) of the mean value of SOFT. These results suggest that credit rating analysts are more likely to make credit risk *increasing* soft adjustments when firms provide more disclosure on debt-related topics. These results further suggest that when managers provide more discussion on earnings-related topics, credit rating analysts are more likely to make credit risk *decreasing* soft adjustments. Looking across Columns 1-3, we also find that both forward-looking and uncertain disclosure increase the likelihood that credit rating analysts make credit risk *increasing* soft adjustments, yet FLS appears to be the dominant driver. Similar to before, when FLS and UNCERT are included in the same regression (Column 1), only FLS is statistically significant. When we exclude UNCERT (Column 2), FLS continues to load; however, when we exclude FLS (Column 3), UNCERT becomes significant. In terms of economic magnitudes, a one standard deviation increase in FLS (UNCERT) is associated with a 0.01 notch (1.67 notch) increase in SOFT, or 1.5% (298%) of the mean value of SOFT.

Table 4, Panel B reports a changes analysis of the relation between qualitative disclosure and soft adjustments. We continue to find similar results for ΔDEBT yet, in contrast to the results found in Panel A, we again find no empirical evidence for ΔEARNINGS and some evidence for ΔFLS in the absence of ΔUNCERT (Column 2). However, across all three specifications, we find consistent evidence for ΔCOMP and ΔTONE. In Column 1, the coefficient on ΔCOMP is -106.54 and the coefficient on ΔTONE is -14.69; with the coefficient on the former (latter) statistically significant at the 5% (1%) level or better. In terms of economic magnitudes, a one standard deviation increase in ΔCOMP (ΔTONE) is associated with a 0.03 (0.04) notch decrease in SOFT, or 5.3% (6.8%) of the mean value of SOFT. Collectively, these results support our conjecture that credit rating analysts' soft adjustments reflect credit risk relevant information conveyed by qualitative disclosure.[1]

#### 4.2.2 Qualitative Disclosure and Hard Adjustments

Despite the initial results that support our conjectures, we cannot yet conclude that soft adjustments are the mechanism by which analysts impound the information found within credit-relevant qualitative disclosure. That is, we have yet to rule other whether or not the information conveyed by qualitative disclosure is uniquely impounded into analysts' soft

[1]While Kraft (2014) provides evidence consistent with soft adjustments reflecting credit risk, we examine the relation between soft adjustments and CDS spreads in our sample and, in untabulated analysis, find that soft adjustments are associated with greater credit spreads.

rating adjustments or if the information merely reflects information similar to their hard rating adjustments. In order to answer this question, we modify the dependent variable in Equation 1 as follows:

$$
\begin{aligned}
HARD_{i,t+1} &= \alpha + \beta_1 DEBT_{i,t} + \beta_2 EARNINGS_{i,t} + \beta_3 FLS_{i,t} \\
&+ \beta_4 UNCERT_{i,t} + \beta_5 COMP_{i,t} + \beta_6 TONE_{i,t} \\
&+ \beta_7 RATE\_IND\_REP_{i,t} + \sum \beta_j HARD\_FIRM\_Controls_{i,t} \\
&+ \sum \beta_k SOFT\_FIRM\_Controls_{i,t} + \epsilon
\end{aligned}
\tag{3}
$$

The results from estimating Equation 3 can be found in Table 5, which follows a similar format to that found in Table 3. Across Columns 1-3, we find no evidence that credit risk relevant qualitative disclosure influences credit analysts' hard ratings adjustments. We view this result as supporting those found in Table 4 on soft rating adjustments which collectively suggest that soft ratings adjustments, as opposed to hard ratings adjustments, are the mechanism by which the information contained in qualitative disclosure makes its way into the actual rating publicly reported by the credit rating agency.

#### 4.2.3 Soft Adjustments and the Repeal of the Reg FD Exemption

We conclude this section by examining how an exogenous shock to credit analysts' information set, the repeal of the Reg FD exemption whereby credit analysts' private access to management was curtailed, affected their information acquisition and processing costs. To conduct this analysis, we modify the change specification version of Equation 2 to include an indicator (RepealRegFD) variable that reflects the repeal period (post October 4, 2010). The variables of interest in Equation 4 are the interactions between the indicator variables and the proxies for qualitative disclosure.

$$
\begin{aligned}
\Delta SOFT_{i,t+1} &= \alpha + \beta_1 \Delta DEBT_{i,t} + \beta_2 \Delta EARNINGS_{i,t} + \beta_3 \Delta FLS_{i,t} \\
&+ \beta_4 \Delta UNCERT_{i,t} + \beta_5 \Delta COMP_{i,t} + \beta_6 \Delta TONE_{i,t} \\
&+ \beta_7 RATE\_IND\_ADJ_{i,t} + \beta_8 RepealRegFD \\
&+ \beta_9 \Delta DEBT * RepealRegFD + \beta_{10} \Delta EARNINGS * RepealRegFD \\
&+ \beta_{11} \Delta FLS * RepealRegFD + \beta_{12} \Delta UNCERT * RepealRegFD \\
&+ \beta_{13} \Delta COMP * RepealRegFD + \beta_{14} \Delta TONE * RepealRegFD \\
&+ \sum \beta_j HARD\_FIRM\_Controls_{i,t} \\
&+ \sum \beta_k SOFT\_FIRM\_Controls_{i,t} + \epsilon
\end{aligned} \tag{4}
$$

The results of estimating Equation 4 can be found in Table 6. We find in Column 1 that the coefficient on ΔEARNINGS*RepealRegFD is -60.76 and the coefficient on ΔUNCERT*RepealRegFD is 48.93, with the former (latter) coefficient statistically significant at the 10% (5%) level or better. Similar results are found in Column 3. In Column 2, when ΔUNCERT is excluded, the coefficient on ΔFLS*RepealRegFD is 1.86 and is statistically significant at the 10% level. While the results from the changes analysis in Table 4, Panel B suggest that credit analysts cultivate risk relevant information from qualitative disclosure pertaining to debt, competition, and optimism, these results suggest that analysts acquire and process similar amounts of those forms of information after the repeal of the Reg FD exemption as compared to the period prior to the repeal. However, the results further suggest that credit analysts appear to seek out and impound credit risk relevant qualitative disclosure pertaining to earnings, forward-looking information, and uncertainty to a greater degree once their information advantage that gave them private access to management was removed.

## 4.3 Ratings Change Informativeness and the Repeal of the Reg FD Exemption

We conclude the study by examining how the repeal of the Reg FD exemption impacted the informativeness of credit ratings that involved soft adjustments and greater levels of credit risk relevant qualitative disclosure. We focus on a sample of 210 downgrades that involve soft rating adjustments since upgrades are generally less informative (Holthausen and Leftwich (1986); Hand et al. (1992); Dichev and Piotroski (2001)). Each issuer rating change constitutes one sample observation. Our sample selection also requires the availability of daily stock returns data for the sample firms in order to compute abnormal stock returns. The average downgrade lowers the rating by 1.3 notches, which reflects a higher number on the ratings scale (i.e., AAA = 1, AA = 2, and so forth), and less than ten percent of downgrades involve revisions from investment grade to speculative grade or vice versa. Following the research design in Jorion et al. (2005) and Dimitrov et al. (2014), we estimate a regression of the following form:

$$\begin{aligned} CAR_{i,t} &= \alpha_0 + \beta_1 RATE\_CHANGE_{i,t} + \beta_2 RepealRegFD_{i,t} + \beta_3 NonZeroSOFT_{i,t} \\ &+ \beta_4 NonZeroSOFT * RepealRegFD_{i,t} + \beta_3 INV\_GRADE_{i,t} \\ &+ \beta_3 PRIOR\_RATE_{i,t} + \beta_4 DAYS_{i,t} + \epsilon \end{aligned} \tag{5}$$

CAR is the cumulative stock return over the three day window (-1,+1) around the rating change less the corresponding return on the CRSP value-weighted index. RATE_CHANGE is the size of the rating change, which is the difference between the numerical value of the new rating and that of the old rating of the same issuer. NonZeroSOFT is a dummy variable equal to one if the absolute value of SOFT is greater than zero, and zero otherwise.[2] INV_GRADE is a dummy variable equal to one if a rating is revised from investment grade to speculative grade or vice versa, and zero otherwise. PRIOR_RATE is the prior rating before the change

[2] In untabulated analysis, we find that the characteristics of firms with NonZeroSOFT equal to one are largely indistinguishable from firms with NonZeroSOFT equal to zero.

and DAYS is the natural log of the number of days since the previous rating change.

Ceteris paribus, the larger is the RATE_CHANGE variable, the larger the stock price response should be. Consistent with Jorion et al. (2005), we expect a negative stock price response for rating downgrades. If announcments of rating downgrades are more (less) informative for firms with non-zero SOFT adjustments, then we would expect the coefficient on NonZeroSOFT to also be negative (positive). The interaction term is intended to capture the relative informativeness of credit rating changes that involve soft adjustments after the repeal of the Reg FD exemption.

In addition, we estimate a variation of Equation 5 that replaces NonZeroSOFT with an arguably more direct overall proxy of the relation between SOFT and the six attributes of qualitative disclosure we measure. Using factor and principal components analysis, we capture the common variation across SOFT and the six measures by extracting either their first factor or principal component. We code a dummy variable, FACTOR (PRIN_COMP), to include in Equation 6 that equals one if the extracted factor (component) is greater than the sample median, and is zero otherwise.

$$\begin{aligned} CAR_{i,t} &= \alpha_0 + \beta_1 RATE\_CHANGE_{i,t} + \beta_2 RepealRegFD_{i,t} + \beta_3 FACTOR|PRIN\_COMP_{i,t} \\ &+ \beta_4 FACTOR|PRIN\_COMP * RepealRegFD_{i,t} + \beta_3 INV\_GRADE_{i,t} \\ &+ \beta_3 PRIOR\_RATE_{i,t} + \beta_4 DAYS_{i,t} + \epsilon \end{aligned} \tag{6}$$

Similarly, if announcements of rating downgrades are more (less) informative for firms with greater amounts of qualitative disclosure, then we would expect the coefficient on FACTOR or PRIN_COMP to be negative (positive). As before, the interaction term is intended to capture the relative informativeness of credit rating changes that involve greater levels of credit risk relevant qualitative disclosure after the repeal of the Reg FD exemption.

Table 7 presents the results of estimating Equations 5 and 6. In Column 1, we include a baseline specification that excludes NonZeroSoft, FACTOR, and PRIN_COMP. The coefficient on RATE_CHANGE is -0.027 and is statistically significant at the 10% level or better, which suggests the market responds negatively to rating downgrades. We see similar results for RATE_CHANGE across all four columns.

Column 2 estimates Equation 5 and therefore presents the market reaction to downgrades when our first variable of interest, NonZeroSOFT, is included in the specification. The coefficient on NonZeroSOFT is -0.042 and is statistically significant at the 5% level or better. The coefficient on the interaction term, NonZeroSOFT*RepealRegFD, is 0.066 and is statistically significant at the 5% level or better. Column 3 estimates Equation 6 and therefore presents the market reaction to downgrades when our second variable of interest, FACTOR, is included in the specification. The coefficient on FACTOR is -0.045 and is statistically significant at the 5% level or better. The coefficient on the interaction term, FACTOR*RepealRegFD, is 0.077 and is statistically significant at the 5% level or better. Column 4 presents the market reaction to downgrades when our third variable of interest, PRIN_COMP, is included in the specification. The coefficient on PRIN_COMP is -0.044 and is statistically significant at the 5% level or better. The coefficient on the interaction term, PRIN_COMP*RepealRegFD, is 0.096 and is statistically significant at the 10% level or better.

Collectively, our results suggest the following. First, rating downgrades that involve soft adjustments prior to the repeal of the Reg RD exemption (NonZeroSOFT) are more informative than downgrades that do not. Second, the greater the level of credit risk relevant qualitative disclosure prior to the repeal of the Reg RD exemption (FACTOR or PRIN_COMP), the more informative the downgrade. These results suggest that credit analysts' cultivation of credit risk relevant information from qualitative disclosure has a beneficial impact on rating informativeness. However, each of the interaction terms suggest the opposite. That is, while higher levels of credit risk relevant qualitative disclosure appear to increase the negative market response to downgrades before the repeal, consistent with Dimitrov et al. (2014), the increase in informativeness is diminished after the repeal, which suggests that the costs of reduced private information supply outweigh the benefits of cultivating credit risk relevant information from qualitative disclosure after the repeal of the exemption.

# 5 Conclusion

Credit ratings represent the judgment of informed and presumably sophisticated financial analysts. Theoretically, efficient evaluations of credit risk should be equal to the expected present discounted value of their cash flows conditional on creditors' information sets, which include qualitative descriptions of firms' operations, prospects, assets-in-place, and earnings (Tetlock et al. (2008)). In this paper, we focus on a single channel by which analysts' judgments of firms' credit risk are likely to be influenced: credit risk relevant qualitative disclosure. In so doing, we attempt to determine whether analysts use information extracted from disclosures in borrowers' financial statements in their judgments of firms' credit risk and whether the acquisition and processing of such disclosures makes ratings more informative. While much is known about how analysts quantitatively model their credit rating assessments, little is known about the soft adjustments analysts make prior to publicly releasing a credit rating. Given the ubiquitous use of credit ratings for capital raising activities, from marketing new debt to monitoring existing debt, an understanding of how credit analysts use firms' qualitative disclosure in their soft assessments sheds lights on the process underlying the ratings that have significant implications for firms' access to and cost of capital.

We first validate our proxies for qualitative disclosure by demonstrating their relation to the actual ratings analysts publicly disclose. Then, we investigate whether credit rating analysts employ credit risk relevant information conveyed by qualitative disclosure in making their soft and hard adjustments. This comparison allows us to examine the mechanism by which credit analysts impound qualitative disclosure into their reported ratings, that is, whether qualitative disclosure influences analysts' hard, or quantitative, adjustments versus their soft, or qualitative, adjustments.

Controlling for credit analysts' hard adjustments, firm characteristics that likely influence hard adjustments, and other variables analysts are likely to consider in making their soft adjustments, we find that qualitative disclosure influences analysts' soft credit ratings adjustments. Specifically, we find that credit rating analysts are more likely to make credit risk *increasing* soft adjustments when firms provide more disclosure on debt-related topics.

The results further suggest that when managers provide more discussion on earnings-related topics, credit rating analysts are more likely to make credit risk *decreasing* soft adjustments. We also find that both forward-looking and uncertain disclosure increase the likelihood that credit rating analysts make credit risk *increasing* soft adjustments, yet forward-looking disclosure appears to be the dominant driver. In stark contrast, we find no evidence that credit risk qualitative disclosure impacts credit analysts' hard adjustments, which, combined with the above results, suggests that qualitative disclosure influences the publicly-reported rating through analysts' soft adjustments.

In changes analysis of the relation between qualitative disclosure and soft adjustments, we continue to find similar results for debt-related topics, yet no evidence for earnings-related topics and some evidence for forward-looking statements. However, we find strong evidence that suggests that competition-related topics and disclosure tone influence credit analysts soft adjustments.

We extend the preceding analysis by examining how an exogenous shock to credit analysts' information set, the repeal of the Reg FD exemption whereby credit analysts' private access to management was curtailed, affected their information acquisition and processing costs. The results suggest that credit analysts acquire and process similar amounts of credit risk relevant information from qualitative disclosure pertaining to debt, competition, and optimism after the repeal of the Reg FD exemption as compared to the period prior to the repeal. However, the results further suggest that credit analysts appear to seek out and impound credit risk relevant qualitative disclosure pertaining to earnings, forward-looking information, and uncertainty to a greater degree once their information advantage that gave them private access to management was removed.

Lastly, we examine the informativeness of credit rating changes that involve soft adjustments as well as changes involving greater levels of credit risk relevant qualitative disclosure. Regarding the former, we find that rating downgrades that involve soft adjustments are more informative than those that do not. Regarding the latter, we find that the greater the level of credit risk relevant qualitative disclosure, the more informative the downgrade. In addition, we examine how the repeal of the Reg FD exemption impacted the informativeness of credit ratings. While ratings involving soft adjustments and greater levels of credit risk relevant qualitative disclosure appear to increase the negative market response to downgrades before the repeal, consistent with Dimitrov et al. (2014), the increase in informativeness diminished after the repeal.

Our paper contributes to our understanding of how important information intermediaries, credit analysts, employ qualitative disclosure in forming their soft risk assessments. In this paper, we are able to link qualitative information to the soft adjustments themselves, i.e., precisely where the qualitative information is likely to have the largest impact. In so doing, we are able to examine the mechanism by which qualitative disclosure is reflected in the final, publicly-reported output traditionally studied by academics and consumed by firm stakeholders. Our paper adds to recent work which examines disclosure clienteles (Kalay (2014)) by suggesting a possible disclosure-based mechanism by which firms may attempt to manage the soft adjustments embedded in their reported credit ratings. Our results should be of interest to academics in devising their credit risk models, regulators in creating new standards that may cater to debt clienteles, and managers of firms in choosing how best to convey risk-relevant information to influence the beliefs of credit analysts.

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## APPENDIX A: Rating Grid by Moody's for Kraft Foods Group, Inc.

Source: Moody's Financial Metrics

| | | | Based on 'As Reported' financial data | | Based on 'As Adjusted' financial data | |
|---|---|---|---|---|---|---|
| **Factor** | **Sub-Factor** | **Weight** | **Sub-Factor** | **Grid-Indicated Rating** | **Sub-Factor** | **Grid-Indicated Rating** |
| SCALE AND DIVERSIFICATION | Total Sales (USD Billion) | 20% | $18.10 | A | $18.10 | A |
| | Geographic Diversification | 12% | Ba | Ba | Ba | Ba |
| | Segmental Diversification | 12% | A | A | A | A |
| FRANCHISE STRENGTH AND | Market Share | 7% | Aaa | Aaa | Aaa | Aaa |
| POTENTIAL | Category Assessment | 7% | Aa | Aa | Aa | Aa |
| PROFITABILITY | EBIT Margin | 7% | 23.00% | Aa | 19.04% | A |
| FINANCIAL POLICY | Financial Policy | 14% | Baa | Baa | Baa | Baa |
| LEVERAGE AND COVERAGE | Debt / EBITDA | 7% | 2.20x | A | 2.92x | Baa |
| | RCF / Net Debt | 7% | 13.98% | B | 14.94% | B |
| | EBIT / Interest Expense | 7% | 8.37x | A | 5.85x | Baa |

| | | | |
|---|---|---|---|
| **Indicated Rating (reported)** | **A3** | | |
| *numerical value* | *7* | | |
| **Indicated Rating (adjusted)** | | | **Baa1** |
| *numerical value* | **HARD = +1** | | *8* |
| **Actual Rating** | | | **Baa2** |
| *numerical value* | **SOFT = +1** | | *9* |

## APPENDIX B: WORD LISTS BY TOPIC

Below are the word lists by topic category used to construct the proxies for qualitative disclosure used in the study.

**DEBT**

Balance sheet, bond, bonds, bondholder, bondholders, cash, cashflow, coverage, debt, debts, default, defaults, financing, funding, debt issue, debt issues, leverage, liability, liabilities, liquid, liquidity, loan, loans, payable, payables, coupon payment, coupon payments, stressed, distressed, fixed income, interest, notes, covenant, covenants, solvent, solvency, credit

**EARNINGS**

Earnings, income, loss, losses, profit, profits, EPS

**FORWARD-LOOKING STATEMENT**

Anticipate, believe, could, expect, forecast, intend, may, might, plan, project, should, will

*Please refer to Li (2010) for the full list of forward-looking terms.*

**UNCERTAINTY**

Ambiguous, cautious, contingent, depends, doubt, precaution, risky, speculation, uncertain, volatile

*Please refer to Loughran and McDonald (2011) for the full list of uncertainty-related terms.*

**COMPETITION**

Competition, competitor, competitive, compete, competing

*Please refer to Li, Lundholm, and Minnis (2013) for the full list of competition-related terms.*

**TONE**

*Please refer to Loughran and McDonald (2011) for the full list of positive and negative terms.*

## APPENDIX C: VARIABLE DEFINITIONS

| Variable | Definition |
|---|---|
| ***Credit rating variables*** | |
| SOFT | Actual rating less indicated adjusted rating (RAT_IND_ADJ). Greater value implies greater credit risk assessment. |
| HARD | Indicated adjusted rating (RAT_IND_ADJ) less indicated reported rating (RAT_IND_REP). Greater value implies greater credit risk assessment. |
| RATE | Actual, publicly-reported issuer rating by Moody's. |
| RATE_IND_REP | Indicated *reported* issuer rating by Moody's from quantitative modeling *before* quantitative adjustments to underlying financial statement inputs. |
| RATE_IND_ADJ | Indicated *adjusted* issuer rating by Moody's *after* quantitative adjustments to underlying financial statement inputs. |
| ***Qualitative disclosure proxies*** | |
| DEBT | The number of references to a debt-related topic in a firm's 10-K scaled by 10-K total word count. See Appendix C for further detail. |
| EARNINGS | The number of references to an earnings-related topic in a firm's 10-K scaled by 10-K total word count. See Appendix C for further detail. |
| FLS | The number of forward-looking statements in a firm's 10-K scaled by 10-K total sentence count. See Appendix C for further detail. |
| UNCERT | The number of references to an uncertainty-related topic in a firm's 10-K scaled by 10-K total word count. See Appendix C for further detail. |
| COMP | The number of references to a competition-related topic in a firm's 10-K scaled by 10-K total word count. See Appendix C for further detail. |
| TONE | The number of positive less negative words scaled by 10-K word count. See Appendix C for further detail. |
| ***Firm characteristics*** | |
| *Hard controls* | |
| SIZE | Log of total assets. |
| LEV | (Short-term debt + long-term debt) / total assets. |
| MB | Market-book-ratio calculated as market value of equity divided by book value of shareholders' equity. |
| ROA | Operating income / total assets. |
| CFO | Operating cash flow / (short-term debt + long-term debt). |
| TANG | (Inventory + property, plant, and equipment) / total assets. |
| LOSS | Dummy variable equal to one if net income before extraordinary items is negative, and zero otherwise. |
| *Soft controls* | |
| BSEG | Number of business segments. |
| GSEG | Number of geographic segments. |
| IO | Log of the annual average number of shares held by institutional investors at the end of the quarter. |
| MAT | The number of years a firm has appeared in Compustat. |
| HHI | Herfindahl index where greater values imply a more monopolistic industry (less competition). |
| RETVOL | Stock return volatility calculated as standard deviation of daily stock returns. |
| FSD | Measure of financial reporting quality based on the level of financial statement divergence (FSD) from Benford's Law following Amiram et al. (2014). Greater value implies lower financial statement quality. |

## APPENDIX C: VARIABLE DEFINITIONS (cont.)

| ***Price response analysis*** | |
|---|---|
| RATE_CHANGE | The difference between the new rating and prior rating. Between -6 and 6. Greater number implies downgrade (e.g., AAA to AA+ = 2 - 1 = 1). |
| CAR | The cumulative stock return over the three day window (-1,+1) around the rating change less the corresponding return on the CRSP value-weighted index. |
| NonZeroSOFT | Dummy variable equal to one if the absolute value of SOFT is greater than zero, and zero otherwise. |
| FACTOR | Dummy variable equal to one if the first factor derived from SOFT and all six disclosure proxies (DEBT, EARNINGS, FLS, UNCERT, COMP, TONE) is greater than sample median, and zero otherwise. |
| PRIN_COMP | Dummy variable equal to one if the first principal component derived from SOFT and all six disclosure proxies (DEBT, EARNINGS, FLS, UNCERT, COMP, TONE) is greater than sample median, and zero otherwise. |
| PRIOR_RATE | Rating prior to rating change. |
| RepealRegFD | Dummy variable equal to one for observations occuring after October 4, 2010, zero otherwise. |
| INV_GRADE | Dummy variable equal to one if a rating is revised from investment grade to speculative grade or vice versa, and zero otherwise. |
| DAYS | Log of number of days since last rating change. |

## TABLE 1

**Descriptive statistics**

Panel A presents summary information on our sample of 2,526 firm-years (732 firms) over the period from 2002 to 2013 for the main analysis. Panel B presents summary information on our sample of rating changes representing 210 downgrades (145 firms) for the price response analysis. All firm characteristics and textual variables are measured the year prior to the measurement of Moody's ratings and adjustments. See Appendix C for variable definitions.

| Variable | Mean | p25 | p50 | p75 | sd | N |
|---|---|---|---|---|---|---|
| **Panel A** | | | | | | |
| SOFT | 0.56 | 0.00 | 0.50 | 1.00 | 1.70 | 2,526 |
| HARD | 0.29 | 0.00 | 0.00 | 1.00 | 1.10 | 2,526 |
| RATE | 11.00 | 9.00 | 11.00 | 14.00 | 3.40 | 2,526 |
| RATE_IND_REP | 10.00 | 8.00 | 10.00 | 13.00 | 3.50 | 2,526 |
| RATE_IND_ADJ | 10.00 | 8.00 | 11.00 | 13.00 | 3.20 | 2,526 |
| DEBT | 1.3% | 1.1% | 1.3% | 1.5% | 0.4% | 2,526 |
| EARNINGS | 0.5% | 0.4% | 0.5% | 0.6% | 0.2% | 2,526 |
| UNCERT | 1.3% | 1.1% | 1.3% | 1.4% | 0.2% | 2,526 |
| FLS | 23.0% | 20.0% | 23.0% | 26.0% | 3.9% | 2,526 |
| COMP | 0.1% | 0.0% | 0.1% | 0.1% | 0.0% | 2,526 |
| TONE | -0.9% | -1.1% | -0.8% | -0.6% | 0.4% | 2,526 |
| *Firm Controls* | | | | | | |
| SIZE | 8.60 | 7.60 | 8.50 | 9.40 | 1.40 | 2,526 |
| LEV | 0.34 | 0.21 | 0.31 | 0.44 | 0.19 | 2,526 |
| MB | 3.30 | 1.30 | 2.00 | 3.30 | 6.60 | 2,526 |
| ROA | 0.09 | 0.05 | 0.09 | 0.12 | 0.08 | 2,526 |
| CFO | 0.49 | 0.16 | 0.29 | 0.55 | 0.78 | 2,526 |
| TANG | 0.46 | 0.26 | 0.45 | 0.66 | 0.24 | 2,526 |
| LOSS | 0.18 | 0.00 | 0.00 | 0.00 | 0.39 | 2,526 |
| BSEG | 6.40 | 2.00 | 4.00 | 10.00 | 5.90 | 2,526 |
| GSEG | 7.60 | 3.00 | 6.00 | 12.00 | 7.20 | 2,526 |
| IO | 18.00 | 18.00 | 18.00 | 19.00 | 3.40 | 2,526 |
| MAT | 35.00 | 18.00 | 28.00 | 53.00 | 19.00 | 2,526 |
| HHI | 0.30 | 0.13 | 0.23 | 0.40 | 0.24 | 2,526 |
| RETVOL | 0.03 | 0.02 | 0.02 | 0.03 | 0.01 | 2,526 |
| FSD | 0.03 | 0.02 | 0.03 | 0.03 | 0.01 | 2,526 |

## TABLE 1 (cont.)
**Descriptive statistics**

| Variable | Mean | p25 | p50 | p75 | sd | N |
|---|---|---|---|---|---|---|
| **Panel B** | | | | | | |
| RATE_CHANGE | 1.20 | 1.00 | 1.00 | 1.00 | 0.56 | 210 |
| CAR | -0.015 | -0.048 | -0.013 | 0.013 | 0.100 | 210 |
| INV_GRADE | 0.08 | 0.00 | 0.00 | 0.00 | 0.27 | 210 |
| DAYS | 1,163 | 191 | 678 | 1,646 | 1,329 | 210 |

## TABLE 2

**Pearson correlation**

The table presents pairwise Pearson correlation between key variables. All firm characteristics and textual variables are measured the year prior to the measurement of Moody's ratings and adjustments. See Appendix C for variable definitions. * denotes 5% significance.

| | SOFT | RATE | DEBT | EARNINGS | UNCERT | FLS | COMP | TONE | BSEG | GSEG | IO | HHI | RETVOL | MB | FSD | AGE | SIZE | LEV | ROA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SOFT | 1.0000 | | | | | | | | | | | | | | | | | | |
| RATE | 0.3315* | 1.0000 | | | | | | | | | | | | | | | | | |
| DEBT | 0.0097 | 0.3787* | 1.0000 | | | | | | | | | | | | | | | | |
| EARNINGS | -0.1428* | -0.2271* | 0.1447* | 1.0000 | | | | | | | | | | | | | | | |
| UNCERT | 0.0548* | 0.0968* | 0.1094* | 0.2832* | 1.0000 | | | | | | | | | | | | | | |
| FLS | 0.0906* | 0.1293* | 0.0112 | 0.0082 | 0.5025* | 1.0000 | | | | | | | | | | | | | |
| COMP | -0.0092 | 0.0557* | -0.0778* | 0.0227 | 0.2390* | 0.1495* | 1.0000 | | | | | | | | | | | | |
| TONE | -0.0306 | -0.1954* | -0.0005 | 0.1979* | -0.0409* | -0.0467* | -0.0435* | 1.0000 | | | | | | | | | | | |
| BSEG | -0.0836* | -0.2371* | -0.0884* | 0.1100* | -0.0399* | -0.1324* | 0.0842* | 0.0789* | 1.0000 | | | | | | | | | | |
| GSEG | 0.0518* | -0.1916* | -0.1321* | 0.1472* | -0.0063 | -0.0663* | -0.0413* | 0.1192* | 0.2547* | 1.0000 | | | | | | | | | |
| IO | -0.0498* | -0.2734* | -0.0610* | 0.0751* | -0.0404* | -0.0129 | -0.1071* | 0.0610* | 0.0342 | 0.0862* | 1.0000 | | | | | | | | |
| HHI | 0.0454* | -0.0550* | -0.0448* | 0.1613* | 0.0287 | -0.0334 | 0.1135* | -0.0021 | 0.0780* | 0.1463* | 0.0488* | 1.0000 | | | | | | | |
| RETVOL | 0.1406* | 0.5042* | 0.1408* | -0.1969* | 0.0516* | -0.0005 | 0.0584* | -0.1666* | -0.0501* | 0.0331 | -0.1484* | 0.0320 | 1.0000 | | | | | | |
| MB | 0.0012 | -0.0345 | 0.0000 | 0.0592* | 0.0032 | -0.0058 | 0.0291 | -0.0116 | -0.0642* | -0.0275 | 0.0111 | 0.0466* | -0.0831* | 1.0000 | | | | | |
| FSD | 0.0399* | 0.1164* | 0.0365 | -0.0741* | -0.0350 | -0.0070 | -0.0415* | -0.0038 | -0.0594* | -0.1063* | -0.0304 | -0.0736* | 0.0554* | -0.0146 | 1.0000 | | | | |
| AGE | -0.2074* | -0.4978* | -0.1845* | 0.1889* | -0.1296* | -0.1055* | -0.1497* | 0.1461* | 0.2235* | 0.2393* | 0.1881* | 0.1722* | -0.2281* | 0.0159 | -0.0957* | 1.0000 | | | |
| SIZE | -0.0919* | -0.6373* | -0.2085* | 0.0517* | -0.1227* | -0.0209 | -0.1263* | 0.0437* | 0.1500* | 0.1339* | 0.2787* | -0.0357 | -0.3989* | -0.0084 | -0.1171* | 0.4240* | 1.0000 | | |
| LEV | -0.0248 | 0.4671* | 0.3946* | -0.1609* | 0.0013 | 0.0435* | 0.1446* | -0.1446* | -0.2043* | -0.2922* | -0.1628* | -0.0498* | 0.2205* | 0.1543* | 0.0414* | -0.3181* | -0.3001* | 1.0000 | |
| ROA | 0.0375 | -0.4072* | -0.2400* | 0.1419* | -0.0100 | -0.0728* | 0.0779* | 0.1063* | 0.0599* | 0.1518* | 0.1522* | 0.0955* | -0.3552* | 0.1897* | -0.1068* | 0.1175* | 0.1289* | -0.1666* | 1.0000 |
| LOSS | 0.0186 | 0.3443* | 0.1376* | -0.1251* | 0.0494* | 0.0120 | 0.0406* | -0.2117* | -0.1237* | -0.0762* | -0.1417* | 0.0074 | 0.4191* | -0.0147 | 0.0506* | -0.1461* | -0.2145* | 0.2807* | -0.5142* |

## TABLE 3

**Panel A: Moody's publicly-reported rating and qualitative disclosure**

This table displays the results from an ordinary least squares (OLS) estimation where the dependent variable is RATE, Moody's publicly-reported rating. All firm characteristics and textual variables are measured the year prior to the measurement of Moody's ratings and adjustments. See Appendix C for variable definitions. Robust t-statistics are presented in parentheses. ** denotes p<0.01, * denotes p<0.05, + denotes p<0.1.

| Dependent variable | (1)<br>RATE | (2)<br>RATE | (3)<br>RATE |
|---|---|---|---|
| DEBT | 80.614** | 80.392** | 77.446** |
| | (5.483) | (5.502) | (5.230) |
| EARNINGS | -200.543** | -202.467** | -215.385** |
| | (-5.471) | (-6.120) | (-5.873) |
| FLS | 4.019** | 3.892** | |
| | (2.631) | (2.887) | |
| UNCERT | -4.603 | | 31.557 |
| | (-0.167) | | (1.296) |
| COMP | 24.705 | 20.797 | 71.299 |
| | (0.146) | (0.127) | (0.423) |
| TONE | -6.565 | -6.421 | -6.304 |
| | (-0.471) | (-0.462) | (-0.447) |
| RATE_IND_REP | 0.486** | 0.486** | 0.488** |
| | (16.554) | (16.557) | (16.698) |
| | (-5.454) | (-5.463) | (-5.398) |
| Constant | 5.837** | 5.819** | 6.174** |
| | (7.277) | (7.261) | (7.627) |
| Hard Controls | Yes | Yes | Yes |
| Soft Controls | Yes | Yes | Yes |
| Fixed Effects | Year | Year | Year |
| Clustering | Firm | Firm | Firm |
| Observations | 2,526 | 2,526 | 2,526 |
| R-squared | 0.77 | 0.77 | 0.77 |

## TABLE 3

**Panel B: Changes in Moody's publicly-reported rating and changes in qualitative disclosure**

This table displays the results from an ordinary least squares (OLS) estimation where the dependent variable is ΔRATE, the change in Moody's publicly-reported rating. Δ indicates the firm characteristics or textual variable is measured as a change during the year prior to the measurement of Moody's change in soft adjustment. See Appendix C for variable definitions. Robust t-statistics are presented in parentheses. ** denotes p<0.01, * denotes p<0.05, + denotes p<0.1.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | Δ RATE | Δ RATE | Δ RATE |
| Δ DEBT | 8.515* | 8.548* | 7.085+ |
| | (2.179) | (2.183) | (1.808) |
| Δ EARNINGS | -1.395 | -0.885 | -1.689 |
| | (-0.097) | (-0.078) | (-0.117) |
| Δ FLS | 0.787 | 0.799+ | |
| | (1.592) | (1.708) | |
| Δ UNCERT | 0.592 | | 7.134 |
| | (0.059) | | (0.751) |
| Δ COMP | -88.870* | -88.015* | -81.851+ |
| | (-1.994) | (-2.062) | (-1.850) |
| Δ TONE | -14.540** | -14.533** | -14.108** |
| | (-3.063) | (-3.067) | (-2.975) |
| Δ RATE_IND_REP | 0.067** | 0.067** | 0.067** |
| | (5.944) | (5.950) | (5.949) |
| Constant | 0.194 | 0.194 | 0.189 |
| | (0.783) | (0.783) | (0.765) |
| Hard Controls | Yes | Yes | Yes |
| Soft Controls | Yes | Yes | Yes |
| Fixed Effects | Year | Year | Year |
| Clustering | Firm | Firm | Firm |
| Observations | 2,365 | 2,365 | 2,365 |
| R-squared | 0.13 | 0.13 | 0.13 |

## TABLE 4

**Panel A: Moody's soft adjustments and qualitative disclosure**

This table displays the results from an ordinary least squares (OLS) estimation where the dependent variable is SOFT Moody's soft adjustment. All firm characteristics and textual variables are measured the year prior to the measurement of Moody's ratings and adjustments. See Appendix C for variable definitions. Robust t-statistics are presented in parentheses. ** denotes p<0.01, * denotes p<0.05, + denotes p<0.1.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | SOFT | SOFT | SOFT |
| DEBT | 35.367** | 35.984** | 32.608* |
| | (2.825) | (2.901) | (2.581) |
| EARNINGS | -190.590** | -185.523** | -203.096** |
| | (-6.354) | (-6.705) | (-6.754) |
| FLS | 3.399** | 3.734** | |
| | (2.793) | (3.391) | |
| UNCERT | 12.199 | | 42.843* |
| | (0.525) | | (2.038) |
| COMP | -131.531 | -121.117 | -92.407 |
| | (-0.942) | (-0.895) | (-0.661) |
| TONE | -2.472 | -2.877 | -2.225 |
| | (-0.198) | (-0.231) | (-0.174) |
| RATE_IND_ADJ | -0.290** | -0.291** | -0.287** |
| | (-9.845) | (-9.863) | (-9.728) |
| Constant | 2.610* | 2.665* | 2.881** |
| | (2.344) | (2.383) | (2.609) |
| Hard Controls | Yes | Yes | Yes |
| Soft Controls | Yes | Yes | Yes |
| Fixed Effects | Year | Year | Year |
| Clustering | Firm | Firm | Firm |
| Observations | 2,526 | 2,526 | 2,526 |
| R-squared | 0.21 | 0.21 | 0.20 |

## TABLE 4

**Panel B: Changes in Moody's soft adjustments and changes in qualitative disclosure**

This table displays the results from an ordinary least squares (OLS) estimation where the dependent variable is ΔSOFT, the change in Moody's soft adjustment. Δ indicates the firm characteristics or textual variable is measured as a change during the year prior to the measurement of Moody's change in soft adjustment. See Appendix C for variable definitions. Robust t-statistics are presented in parentheses. ** denotes p<0.01, * denotes p<0.05, + denotes p<0.1.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | Δ SOFT | Δ SOFT | Δ SOFT |
| Δ DEBT | 10.302* | 10.611* | 8.848* |
| | (2.483) | (2.542) | (2.115) |
| Δ EARNINGS | -4.519 | 0.252 | -4.816 |
| | (-0.294) | (0.021) | (-0.312) |
| Δ FLS | 0.800 | 0.913+ | |
| | (1.524) | (1.819) | |
| Δ UNCERT | 5.546 | | 12.193 |
| | (0.511) | | (1.175) |
| Δ COMP | -106.536* | -98.528* | -99.393* |
| | (-2.242) | (-2.161) | (-2.110) |
| Δ TONE | -14.691** | -14.628** | -14.253** |
| | (-2.976) | (-2.967) | (-2.893) |
| Δ RATE_IND_ADJ | -0.900** | -0.900** | -0.900** |
| | (-59.420) | (-59.481) | (-59.468) |
| Constant | 0.213 | 0.214 | 0.208 |
| | (0.719) | (0.721) | (0.704) |
| Hard Controls | Yes | Yes | Yes |
| Soft Controls | Yes | Yes | Yes |
| Fixed Effects | Year | Year | Year |
| Clustering | Firm | Firm | Firm |
| Observations | 2,365 | 2,365 | 2,365 |
| R-squared | 0.74 | 0.74 | 0.74 |

## TABLE 5

**Moody's hard adjustments and qualitative disclosure**

This table displays the results from an ordinary least squares (OLS) estimation where the dependent variable is HARD Moody's hard adjustment. All firm characteristics and textual variables are measured the year prior to the measurement of Moody's ratings and adjustments. See Appendix C for variable definitions. Robust t-statistics are presented in parentheses. ** denotes p<0.01, * denotes p<0.05, + denotes p<0.1.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | HARD | HARD | HARD |
| DEBT | 8.837 | 7.831 | 8.034 |
| | (1.022) | (0.915) | (0.933) |
| EARNINGS | 4.322 | -4.394 | 0.560 |
| | (0.233) | (-0.252) | (0.031) |
| FLS | 1.018 | 0.445 | |
| | (1.326) | (0.687) | |
| UNCERT | -20.852 | | -11.688 |
| | (-1.500) | | (-1.008) |
| COMP | 51.704 | 33.998 | 63.513 |
| | (0.544) | (0.362) | (0.671) |
| TONE | 6.945 | 7.599 | 7.012 |
| | (0.990) | (1.091) | (1.012) |
| RATE_IND_REP | -0.116** | -0.116** | -0.116** |
| | (-7.572) | (-7.547) | (-7.546) |
| Constant | 3.285** | 3.203** | 3.370** |
| | (7.394) | (7.133) | (7.570) |
| Hard Controls | Yes | Yes | Yes |
| Soft Controls | Yes | Yes | Yes |
| Fixed Effects | Year | Year | Year |
| Clustering | Firm | Firm | Firm |
| Observations | 2,526 | 2,526 | 2,526 |
| R-squared | 0.17 | 0.17 | 0.17 |

## TABLE 6

**Changes in Moody's soft adjustments and changes in qualitative disclosure around the Repeal of Reg FD**

This table displays the results from an ordinary least squares (OLS) estimation where the dependent variable is ΔSOFT, the change in Moody's soft adjustment. Δ indicates the firm characteristics or textual variable is measured as a change during the year prior to the measurement of Moody's change in soft adjustment. RepealRegFD is a dummy variable equal to one for observations occuring after October 4, 2010, zero otherwise. See Appendix C for variable definitions. Robust t-statistics are presented in parentheses. ** denotes p<0.01, * denotes p<0.05, + denotes p<0.1.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | Δ SOFT | Δ SOFT | Δ SOFT |
| Δ DEBT | 18.083* | 17.389* | 17.672* |
| | (2.557) | (2.451) | (2.517) |
| Δ EARNINGS | 31.097 | 10.320 | 30.664 |
| | (1.048) | (0.505) | (1.038) |
| Δ FLS | 0.298 | -0.194 | |
| | (0.315) | (-0.237) | |
| Δ UNCERT | -23.279 | | -20.531 |
| | (-1.124) | | (-1.135) |
| Δ COMP | -103.061 | -130.582+ | -101.023 |
| | (-1.551) | (-1.949) | (-1.527) |
| Δ TONE | -16.368* | -16.747* | -16.246* |
| | (-2.008) | (-2.060) | (-2.000) |
| RepealRegFD | -0.047 | -0.030 | -0.047 |
| | (-0.623) | (-0.408) | (-0.634) |
| Δ DEBT*RepealRegFD | -12.865 | -10.183 | -14.879 |
| | (-1.292) | (-1.017) | (-1.545) |
| Δ EARNINGS*RepealRegFD | -60.756+ | -18.502 | -60.143+ |
| | (-1.745) | (-0.732) | (-1.734) |
| Δ FLS*RepealRegFD | 0.874 | 1.862+ | |
| | (0.751) | (1.758) | |
| Δ UNCERT*RepealRegFD | 48.932* | | 55.367* |
| | (2.071) | | (2.575) |
| Δ COMP*RepealRegFD | -20.113 | 53.205 | -10.556 |
| | (-0.217) | (0.585) | (-0.114) |
| Δ TONE*RepealRegFD | 4.071 | 4.540 | 4.736 |
| | (0.377) | (0.421) | (0.442) |
| Δ RATE_IND_ADJ | -0.901** | -0.901** | -0.900** |
| | (-59.699) | (-59.763) | (-59.462) |
| Constant | 0.206 | 0.191 | 0.207 |
| | (0.696) | (0.646) | (0.693) |
| Hard Controls | Yes | Yes | Yes |
| Soft Controls | Yes | Yes | Yes |
| Fixed Effects | Year | Year | Year |
| Clustering | Firm | Firm | Firm |
| Observations | 2,365 | 2,365 | 2,365 |
| R-squared | 0.74 | 0.74 | 0.74 |

## TABLE 7

**Stock price response to rating changes before and after Repeal of Reg FD**

This table displays the results from an ordinary least squares (OLS) estimation where the dependent variable is CAR, the cumulative abnormal return. The sample consists of 210 downgrades during the period from 2002 to 2012. RepealRegFD is a dummy variable equal to one for observations occuring after October 4, 2010, zero otherwise. See Appendix C for variable definitions. Robust t-statistics are presented in parentheses. ** denotes p<0.01, * denotes p<0.05, + denotes p<0.1.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | CAR | CAR | CAR | CAR |
| RATE_CHANGE | -0.027+ | -0.029* | -0.027+ | -0.025+ |
| | (-1.781) | (-2.062) | (-1.878) | (-1.780) |
| RepealRegFD | 0.010 | -0.040 | -0.033 | -0.042+ |
| | (0.600) | (-1.253) | (-1.171) | (-1.708) |
| NonZeroSOFT | | -0.042* | | |
| | | (-2.224) | | |
| FACTOR | | | -0.045* | |
| | | | (-2.067) | |
| PRIN_COMP | | | | -0.044* |
| | | | | (-2.018) |
| NonZeroSOFT*RepealRegFD | | 0.066* | | |
| | | (1.993) | | |
| FACTOR*RepealRegFD | | | 0.077* | |
| | | | (2.175) | |
| PRIN_COMP*RepealRegFD | | | | 0.096** |
| | | | | (2.837) |
| INV_GRADE | -0.011 | -0.013 | -0.009 | -0.008 |
| | (-0.605) | (-0.713) | (-0.530) | (-0.462) |
| PRIOR_RATE | -0.004 | -0.004 | -0.004+ | -0.004 |
| | (-1.460) | (-1.593) | (-1.716) | (-1.648) |
| DAYS | 0.004 | 0.004 | 0.003 | 0.003 |
| | (0.535) | (0.595) | (0.348) | (0.393) |
| Constant | 0.019 | 0.058 | 0.064 | 0.057 |
| | (0.308) | (0.898) | (0.964) | (0.872) |
| Hard Controls | No | No | No | No |
| Soft Controls | No | No | No | No |
| Fixed Effects | No | No | No | No |
| Clustering | Firm | Firm | Firm | Firm |
| Observations | 210 | 210 | 210 | 210 |
| R-squared | 0.03 | 0.07 | 0.06 | 0.07 |