Does Media Coverage Affect Credit Rating Change Decisions?

ABSTRACT

We present the first evidence on whether media coverage affects credit rating change decisions by analyzing 622,696 newspaper items published by top U.S. media outlets on S&P 1500 firms. Our results show that negative media coverage has a strong association with credit rating change events but positive media coverage does not. We attribute this result primarily to media's opinion formation and sentiment sourcing role. Credit rating agencies apparently note such negative market sentiment and factor it in their rating change decisions.

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I. Introduction

We provide the first evidence on how media coverage affects credit rating change decisions. Credit ratings convey a credible signal to the market because they can predict the likelihood of defaults and future business potential (Becker and Milbourn, 2011). Credit rating agencies (CRAs) are tasked with handling the sensitive decision of assigning a credit rating score. However, the literature contends that the prevalence of an issuer-pay model in the credit rating industry could impair a CRA's rating decision and questions the objectivity of the rating mechanism. Assigning a rating score appears to be a delicate issue. Presumably a decision to change a credit rating score can be more contentious because of its signaling value and the subsequent impacts on a firm's future investments, investor decisions, and a CRA's profitability.

How does a CRA handle such decisions? All major CRAs assert that they value their reputational capital, which guides their rating change decisions (Becker and Milbourn, 2011; Pittman, 2008). Yet, recent empirical studies suggest that no conclusive evidence exists for such a claim and CRAs' decisions may be guided by rating fees paid by the clients (Becker and Milbourn, 2011; Bae, Kang, and Wang, 2015). Market perception of the client firm may play an important role in the CRA's balancing act of preserving self-reputation and generating rating fees. In this study, we focus on a firm's independent media coverage as a measure of market perception and examine how it affects a CRA's credit rating change decision.

Although investigating media's role on credit rating decisions is intriguing, a challenge exists in establishing a causal relation due to endogeneity concerns. The media may be able to anticipate a credit rating change and publish news accordingly. This could lead to an endogenous relation between media coverage and a CRA's rating change decision in the way of reverse causality. Considering the importance of addressing endogeneity issue in this study, we briefly discuss the steps taken to mitigate this concern at the outset. Following Liu and McConnell (2013), we first address this issue by taking an instrumental variable approach. We use 'media expert' as a reasonable instrument, which satisfies the conditions for both inclusion and exclusion restrictions.[1] We find that the coefficient of negative media coverage remains significant in the instrument variable setup, which implies that our results are robust despite the concern of reverse causality. Secondly, we examine the impact of lagged media coverage by several quarters on CRA rating change decisions. The media are likely to publish negative news articles solely in anticipation of rating change decisions more than one quarter before the actual event date. Our results show that lagged negative media coverage of up to one year affects a CRA's decision, which alleviates the concern of reverse causality to a large extent. Another source of endogeneity is the omitted variable bias. To address this issue, we include a comprehensive list of control variables in our multivariate analysis. Further, we employ firm fixed effect models to alleviate the endogeneity bias (Bae, Kang, and Wang, 2011).

We now introduce the dynamics between media coverage and a CRA's rating change decision. A burgeoning literature advocates that independent media coverage can affect a firm's reputational capital by forming opinions in the mindsets of investors and other market participants. The media literature shows that independent media coverage, especially negatively-toned news stories, can influence stock prices, trading activities, and investor opinions (Dyck, Volchkova, and

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[1] Media expert is a dummy variable that takes the value of one if a firm has a media expert on its board of directors. Liu and McConnell's (2013) choice of instrument variable is motivated by Gurun (2015). Gurun finds that firms with at least one media expert on their boards receive less negative media coverage (*addressing the inclusion restriction*). Similar to the arguments of Liu and McConnell, however, we expect no correlation between the presence of media expert on the board and a CRA's rating decision. A CRA is unlikely to consider the presence of a media expert in firm as a primary factor when making a rating change decision (*addressing the exclusion restriction*).

Zingales, 2008; Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Engelberg and Parsons, 2011; Liu and McConnell, 2013). Therefore, conventional wisdom suggests that CRAs pay attention to firm-specific media coverage in order to integrate market sentiment and investor opinion in their rating change decisions. To the best of our knowledge, no empirical evidence exists to support this view. We hypothesize that negative media coverage of a firm significantly affects a CRA's credit rating change decisions. Understanding this relation requires examining a CRA's dilemma when deciding on a rating score.[2]

In a recent theoretical paper, Goel and Thakor (2015) explore the complexities involved in a CRA's rating decision. In their model, a CRA's objective is to balance the divergent goals of a firm and its prospective investors. Although a firm wants a higher credit rating to benefit from a lower cost of capital and favorable business opportunities, prospective investors want a true rating to make more informed decisions. Striking a balance between these divergent goals becomes more complicated given that most of a CRA's fees come from the firms they rate (Bae, Kang, and Wang, 2015). We contend that negative media coverage influences this balancing act. In light of Goel and Thakor's theoretical model, we present two plausible arguments that can explain the relation between media coverage and a CRA's rating change decisions: (1) media's opinion formation and sentiment sourcing argument, and (2) the ratings shopping and diminished media influence argument. We present a more detail discussion on these arguments in Section II and Appendix A.

The media's opinion formation and sentiment sourcing argument suggests that independent

[2] The credit rating literature presents various theoretical works that cover different aspects of credit rating dynamics including: reputational capital and rating quality (Mathis, McAndrews, and Rochet, 2009; Bar-Isaac and Shapiro, 2013); ratings shopping (Skreta and Veldkamp, 2009; Sangiorgi and Spatt, 2012; Fulghieri, Strobl, and Xia, 2014); competition among CRAs (Bolton, Freixas, and Shapiro, 2012); credit rating standards and regulations (Opp, Opp, and Harris, 2013); and rating disclosure decisions (Faure-Grimaud, Peyrache, and Quesada, 2009).

media coverage captures and at least partly forms the sentiment of investors and other market participants. Failing to recognize media induced firm-specific opinions and market sentiment could affect a CRA's reputation. Thus, independent media coverage could be an important factor in a CRA's credit rating change decisions. The other viewpoint (i.e., the ratings shopping and diminished media influence argument) is based on the phenomenon of ratings shopping by firms. An issuer is likely to shop for the best ratings. Under this scenario, irrespective of the media coverage on the issuing firm, CRAs would like to assign inflated ratings to please and attract clients. According to this argument, an insignificant relation exists between media coverage and rating change decisions.[3]

Further, in light with the literature on media coverage (Tetlock, 2007; Loughran and McDonald, 2011), we propose that mainly negatively-toned media coverage matters in making credit rating change decisions. This view is also consistent with the reputation story as discussed by Smith and Walter (2002) and Becker and Milbourn (2011). If the market contains negative news about a firm, a CRA seeking to preserve its reputational capital could be more inclined to revisit a firm's rating.

To examine our primary hypothesis that media coverage affects credit rating change decisions, we collect and analyze 622,696 newspaper items published by top U.S. media outlets on S&P 1500 firms between 1990 and 2009. Our results show that lagged negative media coverage has a strong association with S&P credit rating changes but positive media coverage does not. We

[3] Spatt (2009) contends that under the current set-up of the U.S. credit rating market, the ratings shopping phenomenon is less likely to occur. Given that S&P and Moody's Investment Service publish the credit ratings of most listed firms irrespective of a firm's decision to pay, ratings shopping tends to be less effective in influencing a CRA's rating decision. Bongaerts, Cremers, and Goetzmann (2012) find no empirical support for the ratings shopping phenomenon. Becker and Milbourn (2011) also rule out the possibility of ratings shopping when explaining their results.

attribute this finding to the media's opinion formation and sentiment sourcing role. Independent media coverage, especially negative news, effectively captures a firm's market sentiment and plays a role in opinion formation among market participants. CRAs often note such negative market sentiment and incorporate it into their rating change decisions. We also find that lagged media coverage of up to one year affects a CRA's decision implying that CRAs closely observe the evolution of market sentiment before making a decision. This finding is consistent with the view that CRAs follow a through-the-cycle approach to maintain rating stability (Altman and Rijken, 2004).

To ensure the robustness of our results, we perform a similar analysis using bond level credit rating data. Considering bond level credit rating data from all three major rating agencies (i.e., S&P, Moody's, and Fitch) enables us to examine the effect of the ratings shopping phenomenon more explicitly. Our results show that negative media coverage significantly affects all three CRAs in a similar fashion. An implication of this finding is that negative media coverage dominates the effects of the ratings shopping phenomenon in CRAs' credit rating decisions.[4] To test the effectiveness of negative media coverage, we further examine its effect on bond spreads. Our result shows that negative media coverage increases bond spreads, which reinforces the media's opinion formation and sentiment sourcing role.

Our study contributes to the literature in several ways. First, although the credit rating literature identifies various determinants including macroeconomic factors, governance structure, and firm performance (Matthies, 2013), it is silent on the effect of firm-specific market sentiment on rating change decisions. Our study seeks to fill this gap by showing that firm-specific negative

[4] Bongaerts, Cremers, and Goetzmann (2012) use a similar approach to test the effectiveness of ratings shopping strategy. They examine the impact of an individual agency's (i.e., S&P, Moody's, and Fitch) rating changes on credit spread changes.

media coverage, which represents a firm's market sentiment, helps to explain a CRA's credit rating change decisions. Second, our results shed light on the dilemma faced by CRAs when making rating change decisions by striking a balance between the divergent goals of the rated firm and its investors. Our evidence is consistent with the view that negative media coverage makes a CRA more careful about its reputational capital, which in turn leads to rating revisions. Third, our study reinforces the findings of earlier studies showing that in the context of firm level and corporate bond ratings, the ratings shopping phenomenon does not play a significant role. Although recent empirical findings downplay the impact of a ratings shopping strategy on the quality of corporate bonds' credit ratings, regulators and investors are wary of such an opportunistic strategy, which is inherent to the issuer-pay model.

II. Background and Relevant Conjectures

Our study concerns the major themes of media coverage and credit rating, which have drawn considerable interest among practitioners and academics (Becker and Milbourn, 2011; Fang, Peress, and Zheng, 2014). The media serve as a channel for revealing information about capital markets. Conventional wisdom suggests that CRAs could pay attention to media coverage as a source of additional information and firm-specific market sentiments. The remainder of Section II is organized as follows. First, we focus on the importance and traditional determinants of credit ratings and rating change. In the following sub-section, we investigate how media coverage affects the equilibrium condition in a credit rating decision. Finally, we identify the plausible channels that shape the relation between media coverage and credit rating changes.

A. Importance and Determinants of Credit Ratings and Rating Changes

Given that the functioning of an efficient market relies on credible information flow, arguably CRAs play a critical role in the proper functioning of capital markets (Bae, Kang, and Wang, 2015). As Becker and Milbourn (2011, p. 499) suggest, "Issuers seek ratings for a number of reasons including to improve the marketability or pricing of their financial obligations, to increase their trustworthiness to business counterparties, or to sell securities to investors with preferences over ratings." Kisgen and Strahan (2010) further show that a good credit rating can reduce a firm's cost of capital. Accurate credit ratings can also be helpful to prospective investors, regulators, and other market participants. As Kisgen and Strahan (p. 4330) note, credit ratings can predict a firm's default probability and "are significant predictors of yield to maturity beyond the information contained in publicly available financial variables."

Some early studies explore the factors that could affect a credit rating. Matthies (2013) presents a detailed review of these studies. He separates the determinants of credit ratings into three main categories: (1) financial ratios and financial data such as leverage, liquidity, and firm size (Blume, Lim, and Mackinlay, 1998); (2) corporate governance mechanisms such as ownership structure and board independence (Bhojraj and Sengupta, 2003; Ashbaugh-Skaife, Collins, and LaFond, 2006); and (3) macroeconomic factors that could influence credit ratings such as gross domestic product (GDP) growth measures (Amato and Furfine, 2004).

To our knowledge, no study links media coverage to firm level credit rating changes. Our study aims to fill this gap. The extant literature shows that media coverage can sway investor sentiment, play a corporate governance role, and influence managerial actions.[5] As Tetlock, Saar-

[5] See for example, Tetlock (2007), Fang and Peress (2009), Peress (2014), Engelberg and Parsons (2011), Dyck, Volchkova, and Zingales (2008), and Kuhnen and Nissen (2012).

Tsechansky, and Macskassy (2008) observe, media coverage could contain certain soft information that other publicly available information does not capture. It can also process the information in a way that can sway the mindset of investors, regulators, and other decision makers such as CRAs (Engelberg and Parsons, 2011).

B. The Effect of Media Coverage on the Equilibrium Condition in Rating Decisions

The literature suggests that a credit rating affects both investors and firms (Bae, Kang, and Wang, 2015). Goel and Thakor (2015) develop a theoretical framework that integrates the divergent objectives of investors and firms with respect to a rating decision. Although the thrust of their work is to present a theoretical argument to explain the rationale behind assigning coarse ratings, the authors also develop an equilibrium condition that shapes a CRA's credit rating decision. The equilibrium condition is achieved by maximizing a CRA's objective function, which is a weighted average of the social value of a rating and the rating's value to a firm. A rating's social value refers to the perceived benefits to the prospective investors and other stakeholders from a credit rating. A rating's value to a firm refers to the benefits that could accrue owing to a good credit rating. We contend that a CAR's reputational concern plays an important role in balancing these two components and hence maximizing a CRA's objective function. Given that an indifferent attitude toward client specific negative news can result in reputational damage to a CRA, negative media coverage is likely to affect the equilibrium conditions in rating decisions. We present a more detail discussion on this topic in Appendix A.

However, an alternative viewpoint is possible. If a CRA perceives that its reputational loss would be lower despite assigning a poorer quality (i.e., less accurate) rating to please an issuer or to reduce the cost of a detailed analysis, it might be less inclined to change the rating despite negative media coverage on an issuer. Such possibilities exist in the presence of increased competition in the credit rating market (Becker and Milbourn, 2011; Bar-Isaac and Shapiro, 2013). Further, the ratings shopping phenomenon could also prompt a CRA to inflate the rating of an issuer irrespective of the tone of media coverage. We elaborate on these possibilities below.

C. The Link between Media Coverage and CRA Change Decisions: Competing Arguments

We organize the above discussion into two competing arguments: (1) the media's opinion formation and sentiment sourcing argument and (2) the ratings shopping and diminished media influence argument. These arguments highlight the plausible relation between media coverage and a CRA's credit rating change decisions.

C.1. The media's opinion formation and sentiment sourcing argument

As previously discussed, we view that the media can directly or indirectly influence CRAs either because of their information processing attributes or their capability of forming and representing market sentiment. We term this situation as the media's opinion formation and sentiment sourcing role. Earlier studies show that negative media coverage matters the most in terms of affecting investor opinions, stock returns, and trading activities, but such studies largely ignore or discount media coverage with a positive tone (Tetlock, 2007; Loughran and McDonald, 2011). Accordingly, our analysis mainly focuses on negatively-toned articles in newspapers. We contend that if a firm receives negative newspaper coverage, such coverage could influence a CRA to downgrade a firm's rating. Failing to do so could reduce the social value component of a CRA's objective function disproportionately and could subsequently reduce the overall value generated from a rating. Conventional wisdom suggests that a credit rating's social value depends on a CRA's reputation. If a CRA does not pay attention to the firm-specific market sentiment, it might lose its credibility and reputation. In turn, this could influence a CRA to revise its credit rating score downward in the event of negative media coverage on an issuer as shown in Figure A1 (Appendix A). Thus, according to the media's opinion formation and sentiment sourcing argument, we expect a significant relation between negative media coverage and a CRA's rating change decisions.

An alternative view is that if a CRA does not want to downgrade the rating score after strong negative sentiment in the marketplace, the loss in the rating's social value might be compensated by a similar increase in a firm's rating value. Such an argument is less convincing. If strong negative media coverage occurs, an inflated credit rating is unlikely to allow a firm to maintain or lower its cost of capital. Under this circumstance, a CRA should revise the credit rating and maintain its reputational capital, which in turn would maximize its objective function.

Some early studies provide indirect support for the above arguments. These studies show that CRAs are concerned about their reputations and try to provide honest and accurate ratings to uphold the reputations of their ratings quality (Smith and Walter, 2002). However, market participants cannot always easily validate the rating quality. As Becker and Milbourn (2011, p. 287) note, "Because ratings predict future default events, which are infrequent and can be far off in the future, feedback about the accuracy of ratings is slow and imprecise." Therefore, a safer bet is for a CRA to assign a credit rating that is consistent with market sentiment. Such a strategy should make the CRA's decision less questionable and increase a rating's social value. Because media coverage reflects a firm's market sentiment, CRAs are likely to consider the media's view.

C.2. The ratings shopping and diminished media influence argument

Another phenomenon that can govern the relation between media coverage and credit rating change decisions is the prevalence of ratings shopping. The credit rating industry follows an issuer-pay model that draws criticism because published ratings could be biased as the current model encourages ratings shopping. Critics of the issuer-pay model suggest that under the current practice, an issuer can shop around and purchase the best rating from a CRA (Spatt, 2009). In a theoretical paper, Skreta and Veldkamp (2009) show that ratings shopping can affect the quality of ratings in the structured finance market, especially when the securities are more complex to evaluate. Yet, Becker and Milbourn (2011) suggest that while ratings shopping can have a significant effect in the market for structured products, its effect is likely to be marginal for the corporate securities and overall corporate credit rating that we examine in this paper. Both Becker and Milbourn (2011) and Bongaerts, Cremers and Goetzman (2012) contend that irrespective of issuer payment, Moody's and S&P rate almost all taxable corporate bonds publicly issued in the United States. Although the possibility of obtaining a rating from Fitch provides an opportunity for ratings shopping to an issuer, the availability of solicited or unsolicited ratings from the other two major players reduces the benefits of ratings shopping.

Empirical evidence consistently shows that maleficent effects of ratings shopping are less evident in the corporate bond market. For example, Becker and Milbourn (2011), who examine the effect of increased competition in the credit rating market on firm credit rating and bond rating quality, conclude that the ratings shopping phenomenon does not explain their empirical results. Using a sample of corporate bond ratings between 2000 and 2008, Bongaerts, Cremers, and Goetzman (2012) examine the hypotheses involving ratings shopping, information production, and regulatory certification. Their evidence shows that while Fitch ratings tend to be higher than those issued by Moody's and S&P, an additional rating by Fitch does not significantly affect credit spreads. These findings are consistent with the empirical evidence reported by Cantor and Packer (1997) and Covitz and Harrison (2003).

The dynamics of ratings shopping can be explained with the help of a CRA's objective function as presented in equation A1 (Appendix A). The primary objective of an issuer's ratings shopping strategy is to have a more favorable credit rating with the hope that it would reduce the issuer's overall cost of capital, which would increase the second component of the objective function (i.e., the rating's value to a firm). However, the inherent assumption in the ratings shopping argument is that the issuer purchases an inflated rating from a CRA. While doing so, a CRA has to ignore the negative media pressure to some extent. Therefore, the prevalence of the ratings shopping phenomenon predicts a weak or no relation between media coverage and a CRA's rating change decisions.[6]

III. Data and Methodology

This section presents a detailed discussion of our data sources, variables, and methodology. It also presents summary statistics about the main variables.

A. Initial Sample and Data Sources

Our initial sample consists of all firms included in the ExecuComp database as of 2010 and uses ratings data until 2009.[7] The ExecuComp database covers the firms included in the S&P 1500 Index and retains coverage of firms that ceased being part of this index. ExecuComp contains 2,843 firms, both active and inactive. Due to a different regulatory set-up, we drop firms belonging

[6] The ratings shopping strategy is likely to be rendered ineffective because Moody's and S&P follow a policy of rating almost all U.S. bonds. Fulghieri, Strobl, and Xia (2014) and Langohr and Langohr (2008) present a detailed discussion on the credit rating process and the dynamics of unsolicited and solicited ratings.

[7] Since the adoption of the Dodd-Frank Wall Street Reform and Consumer Project Act in 2010, Purda (2011, p. 20) notes that "Among the many changes brought by the Act was the provision that rating agencies have the same legal liability as other 'experts' who prepare or certify information on registration statements filed with the Securities Exchange Commission." Because the introduction of the Dodd-Frank Act is likely to affect the quality of credit ratings and how CRAs make rating change decisions, we restrict our sample to 2009. As a future step, examining the media's effect on CRAs' rating change decisions in the post-2010 period would be a worthwhile endeavor but it would require voluminous media data processing and relevant analyses.

to the financial industry (SIC 6000 to 6999) and further exclude firms that do not have media coverage in the Factiva Database. We retrieve firm level control variables from the Compustat Annual and Compustat Quarterly databases and security level control variables from the Center for Research in Security Prices (CRSP) daily database. The Compustat database is the source of the firm level credit rating by Standard & Poor's (S&P).[8] The Mergent Fixed Income Securities Database (FISD), which provides bond ratings by all three major CRAs, is the source of the bond level rating and bond data.

B. Media Search

Consistent with Core, Guay, and Larcker (2008) and Malmendier and Tate (2008), we identify the following set of media sources: *Financial Times, The Wall Street Journal, The Economist, The New York Times, Chicago Sun-Times, The Washington Post*, and *USA Today*. We search these media sources for the firms (2,843 in total) identified using the ExecuComp database and download 622,696 relevant articles from 1990 to 2009. We use the Factiva database for our news article search.[9] Factiva recognizes many spellings and offers suggestions as to what company it believes the user is trying to find. This procedure ensures the results are relevant to the company searched. Our analysis involves articles having a minimum of 50 words of content. When downloading the articles, we ignore duplicates by setting the duplicate option in Factiva to "identical".

[8] Becker and Milbourn (2011) also use only S&P's ratings for their firm level credit assessment.

[9] Core, Guay, and Larcker (2008) rely on Factiva for media coverage. Although Factiva covers most influential media sources, it has limited *Business Week* coverage. The authors show that business magazines contain few articles on specific firms compared to newspapers and newswires.

We use a text search program specifically designed for this study to complete the content analysis. This program searches for specified terms and permits creating search strings containing the operators AND, OR, and NEAR. Thus, our program can search for words within a specific range of other assigned words. A potential issue involving this textual analysis is the set of negative or positive words used in the studies. Some previous studies use Harvard-IV-4 word lists to determine an article's positive and negative tone. More recently, Loughran and McDonald (2011) show that using the Harvard-IV-4 negative and positive word lists has drawbacks in the context of finance studies. The main criticism is that these lists are not specific to business terminology. Accordingly, we adopt the word lists proposed by Loughran and McDonald. When searching for negative words, another challenge is to account for the simple negation of positive words. We also follow Loughran and McDonald's approach to mitigate this issue.

C. Key Variables Used in the Multivariate Analysis

Our main dependent variable is the change in credit rating. As described in Appendix B, all three major CRAs use 'letters' to denote a credit rating level. We follow a similar methodology as proposed by Becker and Milbourn (2011) to convert letter ratings to numerical ratings. A change in credit rating refers to the difference in numerical values between two rating levels in subsequent quarters. We also follow a similar approach for determining bond rating changes. In our specification, a higher letter rating is associated with a lower numerical value. Therefore, a negative change in credit rating refers to an improvement in a firm's credit or bond rating.

Our main independent variable is the tone of newswire articles. Following Liu and McConnell (2013), we count the number of negative words over a quarter before the credit rating changes to measure the tone of newswire stories. We use the negative words as a percentage of total words as our measure of the tone of newswire articles (i.e., the negative words ratio). We follow a similar approach to construct the positive tone variable (i.e., the positive words ratio).

As a robustness check, we use an alternative measure to determine an article's overall tone based on the relative appearance of negative and positive words in an article. The rationale behind this alternative measure is that while forming an opinion about an article's tone, readers consider both negative and positive articles simultaneously.[10] Following Becker and Milbourn (2011), we use various control variables in our multivariate analyses. Appendix C presents these variables.

D. Summary Statistics

Table 1 presents the summary statistics of the study's main variables. We consider a total of 69,115 firm-quarter credit rating levels and 67,853 firm-quarter credit rating changes. Because we need more observations to calculate rating changes (i.e., beginning and ending credit rating level data), the number of observations for the rating change is lower than for the rating level. Of the 67,853 rating change observations, 2,132 events (3.14%) show a negative rating change (e.g., the letter rating changes from A to B, or the numerical rating change is positive), 2,936 events (4.32%) show a positive rating change, and 62,785 events (92.53%) do not show any rating change. Table 1 excludes the statistics for negative, positive, and no rating changes. These statistics are consistent with the conventional wisdom that credit rating changes are infrequent events. CRAs appear to be cautious and show restraint when deciding whether to change a firm's rating because

[10] We follow Malmendier and Tate's (2008) CEO overconfidence variable construction methodology in which they compare two different word lists ('cautious' and 'confident' word lists) to create the CEO overconfidence variable. Accordingly, we compare the number of negative and positive words appearing in each article. If the number of negative words exceeds the number of positive words, we classify it as a negatively toned article. Finally, we divide the number of firm-specific negatively-toned articles by the total number of firm-specific articles within a particular period (e.g., over a quarter) to obtain the negative articles ratio variable. We use a similar approach to compute the positive articles ratio variable.

doing so can substantially affect a firm. Similarly, our summary statistics reveal that positive rating changes are more frequent than negative rating changes.

(Insert Table 1 about here)

On average, we find that a firm has 4.35 negative articles and 1.70 positive articles in a quarter. Similarly, an average news article has more negative words (0.0089) than positive words (0.0038). These statistics show a tendency toward negative news by the media sources, which is consistent with the finding of Loughran and McDonald (2011). The average firm size (total assets) and average annual sales are about $10 billion and $1.8 billion, respectively. Most firms show a positive profitability as revealed by Operating Income/Total Asset and EBITDA/Total Asset. On average, a firm has 32% debt and the inverse interest coverage ratio (Interest/EB ITDA) is less than 1.

Figure 1 presents the quarterly trends in negative and positive news articles around the credit rating upgrades and downgrades in two panels. Panel A of Figure 1 shows that firms experience an increase in both total and negative news articles before rating downgrade events. Also, a very gradual decrease in positive news articles appears before such events. Panel B reveals a different but less dramatic picture involving positive rating changes. A decrease in negative news articles and a very gradual increase in positive news articles occur before a positive rating change event.

(Insert Figure 1 about here)

In general, Figure 1 indicates that a relation between negative news articles and rating changes, especially for the negative rating changes. Apparently, positive news coverage does not change much and hence might not be as informative as negative news coverage. We explore these findings in detail using multivariate analyses in the subsequent sections.

IV. Results and Discussion

In this section we discuss the influence media coverage can have on credit rating decisions. Next, we examine potential endogeneity bias followed by a discussion of the media's opinion building role. Finally, we focus on independent media coverage and bond ratings.

A. Influence of Media Coverage on Credit Rating Change Decisions

In this section, we examine whether independent media (newspaper) coverage influences credit rating change decisions. We explore the role of negative and positive media coverage separately as their impact could vary.

A.1. The role of negative media coverage

Table 2 presents the ordinary least squares (OLS) regression models that examine the association of negative (positive) newspaper coverage with credit rating changes in Panel A (Panel B). Following Becker and Milbourn (2011), we control for industry and year-quarter fixed effects in models (2) to (4) to rule out any overall time trends or pure cross-industry explanations. We use standard errors that are clustered by industry times the year-quarter cell in all the models to account for the correlations within an industry for a particular quarter. The dependent variable is the quarterly change of the firm level S&P credit rating and the main independent variable is the one-quarter lagged negative words ratio in the media, measured quarterly (Lag (Neg News)) in Panel A of Table 2.

(Insert Table 2 about here)

In Panel A, Model 1 presents the base model that examines the effect of negative newspaper coverage only and excludes any other controls. Model 2 includes the year-quarter fixed effect and the industry fixed effect. Model 3 introduces control variables as identified in Becker and Milbourn

(2011). Model 4 adds the squared terms of the control variables and the change in the control variables over two consecutive quarters before the rating change event. Because we mainly focus on the rating change rather than the rating score, including the quarterly change in control variables is important. Model 5 includes the firm-fixed effects to alleviate the concern of omitted firm heterogeneity. Firm-fixed effects should absorb most of the variations in the dependent variable and also make industry fixed-effects redundant.

In all models, we find that the negative newspaper tone variable, Lag (Neg News), has a significantly positive association with the credit rating change variable. The Lag (Neg News) coefficient ranges from 1.936 to 2.739 and all p-values are less than 0.01. According to our credit score mapping scheme, a higher numerical score for a credit rating refers to poorer credit quality. Therefore, our results imply that strong negative newspaper coverage before a rating change event influences a CRA to downgrade its credit score. Our results are robust and stable across all regression models. Our evidence implies that CRAs pay attention to the independent negative media coverage, which represents firm-specific sentiment and can sway investor opinions. Thus, we find support for the media's opinion formation and sentiment sourcing role. This finding is consistent with the literature on newspaper media suggesting that the media are informative and can influence market participants, managers, and regulators.

Our findings also have economic significance. We focus on Model 5, which considers the firm-fixed effect and gives more stringent estimates, to explain the practical relevance of our results. In Model 5, the Lag (Neg News) coefficient is 2.352. If the negative media coverage ratio moves from the 25^{th} to 75^{th} percentile level (i.e., an increase of 0.02 as Table 1 shows), the average credit rating change value would increase by 0.047 (i.e., 0.02 × 2.352). This circumstance corresponds to a one rating step downgrade from A to A– for about one out of 20 firms.

Some control variables also show significant results. For example, a firm with a better credit rating score (Rating), larger asset base (Size), higher operating income (Operating Income/Total Assets), higher cash flow (Cash Flow), and better growth prospects (Market-to-Book Value or MTB) has a better chance of experiencing a more favorable credit rating change. In our specification, a negative coefficient implies a favorable rating change. Conversely, we find that a firm with higher leverage has a greater chance of experiencing a downgrade. However, the coefficients for the interest coverage ratio (Interest/EBITDA) and asset tangibility (TANG) appear counter intuitive. A negative coefficient on the interest coverage ratio (Model 5 with a coefficient of –0.062 and a p-value < 0.01) suggests that a firm with better interest coverage is more likely to face a downgrade. Such an apparently puzzling result could be attributed to industry norms because firms in certain industries maintain a higher interest coverage ratio (Bae, Kang, and Wang, 2015).

Our results also suggest that firms with more tangible assets (TANG) experience more downgrades as shown by Model 5 with a coefficient 0.472 and a p-value < 0.01. The capital structure literature shows that firms with more tangible assets maintain a higher debt level (Frank and Goyal, 2009). These firms might be overleveraged and be more prone to downgrades. Although this situation provides a plausible explanation of the positive association between TANG and a credit rating downgrade, we do not rule out some other possibilities. Given the scope of our study, we do not explore this issue further.[11]

A.2. The role of positive media coverage

[11] Although Becker and Milbourn (2011) and Bae, Kang, and Wang (2015) follow similar methodologies and use the same control variables, they do not report any detailed results. Hence, we cannot compare the coefficients between the various models.

Next, we focus on positive media coverage. Panel B of Table 2 presents the OLS regression models that examine the association of positive newspaper coverage with credit rating changes. The dependent variable is the quarterly change of the firm level S&P credit rating and the main independent variable is the one-quarter lagged positive news ratio coverage in the media, measured quarterly (Lag (Pos News)). Model 1 presents the base model that does not include any other controls. Model 2 includes both the year-quarter fixed effect and the industry fixed effect. Model 3 introduces control variables as identified in Becker and Milbourn (2011). Model 4 adds the squared terms of control variables and the change in control variables over two consecutive quarters before the rating change event. Model 5 includes firm-fixed effects to alleviate the concern of omitted firm heterogeneity.

In all models, we find that the positive newspaper tone variable, Lag (Pos News), does not show any significant association with the credit rating change variable. Our results imply that positive newspaper coverage does not sway a CRA's decision. This result is consistent with the media literature showing that positive media coverage is less effective than negative media coverage or is discounted by investors and market participants. This evidence is also consistent with Panel B of Figure 1, which shows that the appearance of negatively- and positively-toned articles before rating upgrade events. In the same figure, we find a gradual decrease in negatively-toned articles before rating upgrade events, but little change in positively-toned article trends.

B. Addressing Endogeneity Bias

So far we have examined whether independent media coverage can influence a CRA's decision-making process. However, we have not considered endogeneity bias that may be induced due to omitted variables or reverse causality (Bae, Kang, and Wang, 2011). To ensure the robustness of our results, we address these potential endogeneity biases. For example, if some omitted variables affect both media coverage and credit rating scores, then the negative media coverage will not be exogenous to the credit rating score change variable, which is our main dependent variable. Alternatively, a possibility exists that independent media anticipates future credit rating changes and publish articles accordingly. In such a case, reverse causality will occur. When the omitted variables or the reverse causality problems influence our test results, the coefficient estimations from the OLS regression models will be inconsistent and biased. To address these biases, we perform the following tests.

B.1. Firm fixed effect regression

As explained previously, our main focus is on negative media coverage. In order to address the omitted variable issue in the negative media coverage models (Table 2 Panel A, Model 1 to 4), we control for firm fixed effects in the Model 5, and find that lagged negative word ratio (i.e., Lag(Neg News)) still has a significant and positive association with credit rating changes. We also explicitly control for a set of other firm-specific factors (e.g., firm size, firm performance, leverage, and market-to-book value) that could affect both media coverage and credit rating scores, as presented in Model 5 of Table 2. Our results remain robust to these measures and, thus, partially alleviate the endogeneity concern.

B.2. Instrumental variable approach: Two-stage least square regression

The other concern is reverse causality bias. Consistent with the recent credit rating literature (Becker and Milbourn, 2011; Bae, Kang, and Wang, 2015), we follow an instrumental variable approach to address this issue. We resort to the media literature to find a suitable instrument and rely on a concept proposed by Gurun (2015). According to Gurun, the presence of a media expert on the board can influence firm-specific negative media coverage but at the same time may not influence the outcome variable directly. Recently, Liu and McConnell (2013) have employed this instrument variable successfully in a study that examines the influence of media coverage on merger and acquisition (M&A) abandonment decision. In particular, the authors use a dummy variable that takes the value of one if the firm has a media expert on its board of directors (Media_expert). We use the same instrument and, in line with Liu and McConnell, expect no significant correlation between the presence of a media expert on the board and the future credit rating change decision.

To operationalize the media expert variable, we check for media association for the board members. If the CEO or a board member ever has been an employee of a television, radio or newspaper company (with three-digit SIC = 271, 271 or 483), we classify that person as a media expert. We extract relevant information from a firm's annual report, its proxy statement, the Factiva and Lexis-Nexis database, and a web-search. We use three variations of media expert dummy variable. Media_expert1 is equal to one if any of the board members or the CEO is considered as a media expert as stated above. Media_expert2 is equal to one if any of the board members is a media expert; and Media_expert3 is equal to one if the CEO is a media expert.

Table 3 presents the instrumental-variable regression results using two-stage least squares (2SLS). Columns (1) to (3) present the results for first stage regressions and Columns (4) to (6) present the second stage results. Model 1, 2, and 3 of Table 4 present results for the *Media_expert1*, *Media_expert2*, and *Media_expert3* variables, respectively. In all three models, we find that the media expert variable has a significant and negative association with negative media coverage. These results support the notion that firms with at least one media expert on their board receive media coverage with less negative tone (Gurun, 2015; Liu and McConnell, 2013).

(Insert Table 3 about here)

Columns (4) to (6) presents the second stage regression results based on the first stage prediction as shown in Columns (1), (2), and (3), respectively. In all three models, we find that the predicted values of negative media coverage have significantly positive associations with the credit rating change variable. According to our specification, a positive value for the credit rating change variable refers to a decrease in credit quality. Thus, the second stage results imply that negative media coverage influences a CRA's downgrade decisions even after controlling for possible reverse causality bias.

In short, the results for the omitted variables and reverse causality bias support the proposition that the results of our initial analysis as shown in Panel A of Table 2 are not the outcome of spurious correlation between negative media coverage and credit rating changes. In unreported results, we find that estimation coefficients remain similar with using the generalized method of moments (GMM) technique.

C. The Media's Opinion Building Role

So far we have explored the impact of news stories that are published during the quarter before a rating change event. The literature suggests that CRAs do not hastily change a rating. Instead, they take time to assess and assimilate new information and try to avoid any gross mistakes when making rating change decisions, which are attributed to the through-the-cycle methodology used by CRAs (Bae, Kang, and Wang, 2015). As Altman and Rijken (2004, p. 2679) explain, "According to Moody's, through-the-cycle ratings are stable because they are intended to measure default risk over long investment horizons, and because they are changed only when agencies are confident that observed changes in a company's risk profile are likely to be permanent." CRAs need to strike a balance between rating timeliness and rating stability. A frequent rating change could be inconvenient for investors, especially institutional investors, who might need to rebalance their portfolios once a firm's rating changes.

In the context of our study, the above discussion suggests that besides recent media coverage (i.e., news appearing in the previous quarter), relatively older media coverage (i.e., news appearing beyond the last quarter) could also influence a CRA's perception about a firm's creditworthiness. We explore this conjecture by introducing more lagged media coverage variables in the regression models. In line with our earlier findings, we concentrate on negative media coverage. Table 4 presents the relevant results.

(Insert Table 4 about here)

The regression models are similar to the full model as presented in Table 2. We replace the media coverage variable with different lagged variables. For example, Model 1 includes a two-lagged media coverage variable. Similarly Models 2, 3, and 4 include three-, four-, and five-lagged media coverage variables, respectively. Model 1 reports a coefficient of 1.263 (a p-value < 0.01) for Lag2 (Neg News); Model 2 reports a coefficient of 0.898 (a p-value < 0.05) for Lag3 (Neg News); Model 3 reports a coefficient of 0.805 (a p-value < 0.10) for Lag4 (Neg News); and Model 4 reports a coefficient of 0.471 (a p-value > 0.10) for Lag4 (Neg News) variable. Our evidence shows the following: (1) even previous media coverage beyond the last quarter matters in credit rating change decisions; (2) media coverage effects fade when moving away from the rating change event data; and (3) media coverage becomes irrelevant if it is more than a year old. Overall, our results support the notion that CRAs wait before acting on some new developments. Thus, CRAs closely observe how the market sentiment evolves over time before making a rating change. This description is consistent with the through-the-cycle-approach followed by CRAs.

In the above analysis, we primarily focus on the media's opinion formation and sentiment sourcing role. However, our empirical results also shed light on the validity of the ratings shopping and diminished media influence argument. As previously discussed, if a ratings shopping strategy plays an important role in a CRA's rating change decisions, no significant relation should exist between media coverage and rating change. Should a ratings shopping strategy play a dominant role, CRAs would ignore media coverage and decide on rating changes to satisfy the issuers. Our results do not support this view. Yet, given that we have firm level credit rating data from only one CRA (i.e., S&P as in Becker and Milbourn, 2011), these analyses do not permit explicitly examining the validity of the ratings shopping and diminished media influence argument. We overcome this challenge by using bond rating data.

D. Independent Media Coverage and Bond Rating

In this section, we discuss how independent media coverage can affect bond rating changes and bond spreads.

D.1. Effect of independent media coverage on bond rating changes

Our previous analyses focus on the relation between independent media coverage and firm rating. CRAs also rate bonds. Because our main argument is that independent media coverage influences a CRA's decision-making process, we should find similar results with bond rating changes. Thus, an analysis of bond rating changes provides another opportunity to ensure that our results are robust. For the firm level rating analyses, we use rating scores only from S&P. For the bond ratings, we have the scores from all three major CRAs (i.e., S&P, Moody's, and Fitch). This situation provides an opportunity to test whether a ratings shopping strategy dominates media's influence on CRAs' rating change decision.

(Insert Table 5 about here)

Table 5 presents the results that examine the relation between negative media coverage and bond rating changes. First, we use the average bond ratings based on the individual scores assigned by the three major CRAs to calculate bond rating changes. Models 1 to 5 use this measure as the dependent variable. Models 4 and 5 represent more complete models: Model 4 includes an industry effect whereas Model 5 uses a firm fixed effect. In all models, we find that the negatively-toned variable, Lag (Neg News), has a significantly positive association with the bond rating change variable. The Lag (Neg News) coefficients ranges from 10.996 to 6.116 and all p-values are < 0.001. According to our bond score mapping scheme, a higher numerical score for a bond rating means a poorer bond quality. Thus, a positive change in a bond rating score refers to a downgrade. Therefore, our results imply that strong negative newspaper coverage before a rating change event is related to a CRA downgrading a bond rating score. Our results are robust and stable across all regression models as presented in Models 1 to 5.

Our results also have practical significance as illustrated using the results of Model 5, which considers the firm fixed effect and gives more stringent estimates. In Model 5, the Lag (Neg News) coefficient is 6.116. If negative media coverage ratio moves from the 25^{th} to the 75^{th} percentile level (i.e., an increase of 0.02 as Table 1 shows), the average credit rating change value would increase by $(0.02 \times 6.116) = 0.122$ (worsen). This change corresponds to a one rating step downgrade from A to A– of about one out of eight bonds.

We also examine whether our results remain consistent if we consider individual bond rating scores assigned by S&P, Moody's, and Fitch. For the sake of brevity, we present only the full model results (similar to Model 5), which include firm fixed effects. Models 6, 7, and 8 present the results for S&P, Moody's, and Fitch rating changes, respectively. In all three models, we find similar results. As expected, the sample size drops substantially when we use only Fitch rating data (Model 8). This finding is consistent with the view that Fitch typically plays the role of providing a third opinion but it also creates the basis for ratings shopping (Bongaerts, Cremers, and Goetzmann, 2012). Because Fitch rating changes also show similar results as for S&P and Moody's (i.e., Models 6, 7, and 8 all show similar results for Lag (Neg News) variable), this evidence casts doubt on the dominance of a ratings shopping strategy followed by an issuer. That is, we find that the influence of negative media coverage on a CRA's rating change decisions dominates the execution of a ratings shopping strategy, if any. Although not reported here, we also perform similar tests for endogeneity bias (as in Table 3) and find that our results remain robust.

D.2. Effect of independent media coverage on bond spreads

Our main conclusion is that negative media coverage can influence a CRA to revise its rating. While pursuing our analyses, we assume that negative media coverage can influence investors' opinions and can represent their sentiments; hence, a CRA takes note of negative media coverage. However, we are unaware of any previous study verifying the assumption that in the context of a credit or bond rating, negative media coverage influences investor sentiment. Given that testing the appropriateness of this assumption with credit or bond rating data is challenging, we examine the validity of our underlying assumption indirectly using bond spread data. Following Becker and Milbourn (2011), we define a bond spread as a corporate bond's yield to maturity (YTM) minus a government bond's YTM with the closest maturity. Finding that negative media coverage increases the bond spread would imply that investors pay attention to negative media coverage while forming a perception on bond quality.

(Insert Table 6 about here)

Table 6 presents the relevant results that examine the relation between negative media coverage and bond spread. Model 1 includes only the media variable and the average bond rating level as the independent variables. Models 2 and 3 include additional controls to ensure more robust results. Model 2 includes the industry fixed effect, whereas Model 3 accounts for the issue fixed effect. In all three models, we find that negative media coverage has a highly significantly positive effect on bond spreads, with coefficients of Lag (Neg News) ranging from 0.0894 to 0.2848 and p-values of < 0.01. Apparently, negative media coverage influences investors' perceptions of a firm's creditworthiness, which in turn is manifested by a wider bond spread. These results further support the media's opinion formation and sentiment sourcing role.

V. Robustness Tests

In this section, we conduct various robustness tests. Our first tests use alternative regression methodologies followed by tests using different measures for negative media coverage, clustering schemes, and sub-samples based on two time periods and investment grades.

A. Alternative Regression Methodologies

Following Becker and Milbourn (2011) and Bae, Kang, and Wang (2015), we primarily use pooled time-series cross-sectional OLS regression techniques to carry out our analyses. Although carefully specified OLS models lead to robust results and are commonly used in the credit rating literature (Kisgen, 2006), earlier studies also use other regression techniques. To ensure that our results are robust to other regression techniques, we repeat our analyses using two other frequently used regression methodologies: (1) ordered probit model (Blume, Lim, and Mackinlay, 1998) and (2) panel data models (Odders-White and Ready, 2006). An ordered probit model is useful in the sense that it recognizes the hierarchy of credit rating scores, whereas the panel data model recognizes that observations related to the same firm are not independent.

(Insert Table 7 about here)

Table 7 shows the relevant results. For the purpose of brevity, we only report the findings for negative media coverage. Both Models 1 and 2 show the results for the ordered probit model. Model 1 includes industry fixed effects, while Model 2 considers firm fixed effects. Both models show that the coefficient of lagged negative media coverage variable is significantly positive. The results are similar to those reported in Table 2.

Models 3 and 4 present the results for the fixed-effect and random-effect panel data regression models. Although a Hausman test suggests that the fixed-effect model is more appropriate for our sample, we report both the fixed-effect and random-effect results, which are consistent. Again, we find that panel data regression models lead to similar findings as reported in Table 2 in which we use OLS methodology. For both the ordered probit model and panel data model, we perform tests for endogeneity bias by employing the same instruments as in Table 3. Our main findings remain qualitatively similar even after controlling for endogeneity bias. We do not report these results for the sake of brevity but they are available from the authors upon request.

B. Other Robustness Tests

We use several other tests to ensure that our results are robust. First, as explained in section III(C), we use different measures for negative media coverage and total negative articles, namely, the negative articles ratio and total negative articles counts.

(Insert Tables 8 and 9 about here)

Panel A of Tables 8 and 9 presents the relevant results for firm level credit rating and bond credit rating, respectively. From both tables, we find that these alternative measures of media coverage significantly affect a CRA's rating changes. This evidence also supports the media's opinion formation and sentiment sourcing role. Second, we use different clustering schemes to ensure that diverse ways of obtaining the standard errors do not bias our results. Panel B of Tables 8 and 9 presents the relevant results for firm level and bond level credit rating data, respectively. Our results remain consistent irrespective of using different clustering methods. Third, we test our results using different sub-samples based on time periods (1990 to 1999 and 2000 to 2009), firm credit quality (investment grade vs. speculative grade), and firm size (small, medium, and large).

Panel C of Tables 8 and 9 presents the relevant results for firm level and bond level credit rating data, respectively. In Panel C, Models 1 and 2 show the results for the two sub-periods. As the evidence shows, S&P and Moody's dominate the credit rating market during the first period (1990 to 1999). This period occurs before Moody's public listing, which resulted in substantially affecting its ratings policy (Kedia, Rajgopal, and Zhou, 2014). In the post-IPO period (2000 to 2009), Moody's ratings for both corporate bonds and structured finance products became more favorable to issuers compared to S&P's ratings. During the second period (2000 to 2009), Fitch played a more important role in the credit rating market (Becker and Milbourn, 2011), which could have encouraged the ratings shopping phenomenon. However, our results show that the influence of negative media coverage remains significant in both sub-periods.

Panel C of Table 8 and 9 (Models 3, 4, and 5) presents the results for investment grade (IG) ratings, speculative grade (SG) ratings, and changes from investment to speculative grade (IG to SG) ratings. Model 5's results are of particular interest because this model uses a dummy variable as a dependent variable. If a credit rating changes from IG to SG, the value is 1, otherwise it is zero. Bongaerts, Cremers, and Goetzman (2012) find evidence that supports the ratings shopping hypothesis around the IG-SG boundary. Yet, our results show that in this category, media coverage dominates and significantly affects rating change decisions. Models 6, 7, and 8 present results for different firm sizes showing that the media's effect remains consistent across all size groups. Although not reported, we find similar results using probit regression.

VI. Summary and Conclusions

We examine the relation between independent media coverage and credit rating changes. Given that negative media are more influential than positive media, we primarily focus on negative media coverage. The literature shows that credit ratings are important for a firm because they can affect both its cost of capital and future business opportunities. Consequently, firms prefer higher credit ratings. A CRA's rating decision is not straightforward. All three major CRAs publicize that they care about their reputational capital and are objective when assigning a credit score. Yet, CRAs potentially face conflicts of interest as a result of following an issuer-pay model in which the firms being rated pay a rating fee. Such a dilemma is compounded when CRAs need to downgrade a credit rating.

When examining the relation between independent media coverage and credit rating changes, we consider two different arguments. The media's opinion formation and sentiment sourcing argument posits that independent media coverage, especially negative toned news, effectively captures a firm's market sentiment and plays a role in opinion formation among market participants. CRAs consider such negative market sentiment and factor it in their rating change decisions. The ratings shopping and diminished media influence argument posits that issuers try to shop for the best rating. Given that the credit rating market follows an issuer-pay model, the rating agencies want to please the issuer and ignore any unfavorable media coverage on the firm. The first argument suggests a significant relation between media coverage and a CRA's rating change decisions, while the second argument advocates no systematic association.

We examine our conjectures by collecting and analyzing 622,696 newspaper items published by top U.S. media outlets on S&P 1500 firms between 1990 and 2009. Our evidence shows that lagged negative media coverage has a strong association with credit rating change events. Further tests suggest that both the media's opinion formation and sentiment sourcing role and its anticipation role explain our results. Our findings are consistent using various robustness tests. Similar to some other recent studies (Becker and Milbourn, 2011; Bongaerts, Cremers, and Goetzman, 2012), we also find that a ratings shopping strategy does not play a dominant role at least in corporate bond rating markets. To the best of our knowledge, no previous study examines the influence of firm-specific market sentiment on credit rating change decisions.

Our results have both practical and policy implications. Given the importance of credit rating scores, CRAs must be competent and make objective assessments of issuers and their fixed income instruments such as bonds. The Securities and Exchange Commission (SEC) mandates that a CRA must obtain the designation as a Nationally Recognized Statistical Organization (NRSRO), which represents a substantial barrier to entry. Accordingly, the credit rating industry has had only three NRSROs until 2002. Today, the SEC recognizes 10 NRSROs.[12] As the literature shows, the increased competition could not only reduce the incentive for a CRA to assign a more accurate rating but also give an issuer more opportunity for ratings shopping. Under this scenario, having an effective external governance mechanism to restrain a CRA from assigning an inflated rating and to discourage an issuer from shopping for a better rating is important. Our evidence shows that media coverage plays this important role of external governance and suggests that the vigilance by the media helps to ensure some checks and balances in the credit rating industry.

[12] A list of all NRSROs is available on http://www.sec.gov/answers/nrsro.htm.

Appendix A. Media Coverage's Effect on the Equilibrium Condition in Rating Decisions

Goel and Thakor (2015) develop a theoretical framework that integrates the divergent objectives of investors and firms with respect to a rating decision. Although the thrust of their work is to present a theoretical argument to explain the rationale behind assigning coarse ratings, the authors also develop an equilibrium condition that shapes a CRA's credit rating decision. The equilibrium condition is achieved by maximizing a CRA's objective function, which is a weighted average of the social value of a rating and the rating's value to a firm.[13] In the context of our study, we present a modified version of the objective function (Z) below:[14]

$$Z\big(\hat{k}(r), k\big) = \gamma V_s\big(\hat{k}(r), k\big) + \delta V_F\big(\hat{k}(r), k\big) \quad \text{(A1)}$$

The first term on the right side of the objective function denotes the social value of a rating and the second term refers to the rating's value to a firm. The social value of a rating refers to the perceived benefits to the prospective investors and other stakeholders from a credit rating. The value of a rating to a firm refers to the benefits that could accrue due to a good credit rating. Symbols γ and δ are positive constants, which denote the respective weights assigned to social value and firm value by a CRA. As the objective function suggests, both the social value and firm value depend on k and $\hat{k}(r)$. The term k refers to the true firm quality, whereas $\hat{k}(r)$ denotes the perceived firm quality based possibly on the firm level credit rating (r).

Due to reputational concerns, a CRA has the incentive to focus on a firm's overall efficiency and future outlook while determining a rating score. Such reputational concerns could influence a CRA to assign a more accurate rating, which in turn could benefit prospective investors and other stakeholders. Thus, a more accurate rating would lead to an increase in the social value of a rating (V_s), which could also benefit a CRA. If a CRA has a better reputation for providing quality ratings than other CRAs, it could charge a higher fee and attract more clients. Conversely, a CRA might benefit from providing an inflated rating to a firm. A higher credit rating is likely to lower both a firm's cost of capital and its cost of doing business, which in turn could lead to an increase in firm value and existing shareholder wealth. Hence, a firm receiving a favorable credit rating might reward a CRA with more future business opportunities (Becker and Milbourn, 2011; Bae, Kang, and Wang, 2015; Goel and Thakor, 2015). CRAs need to strike a balance between these two divergent objectives.

How does media coverage affect the equilibrium condition in a credit rating decision? We explore this question with the help of two rating scenarios for a single firm 'A'. Assume that a CRA rates firm 'A'

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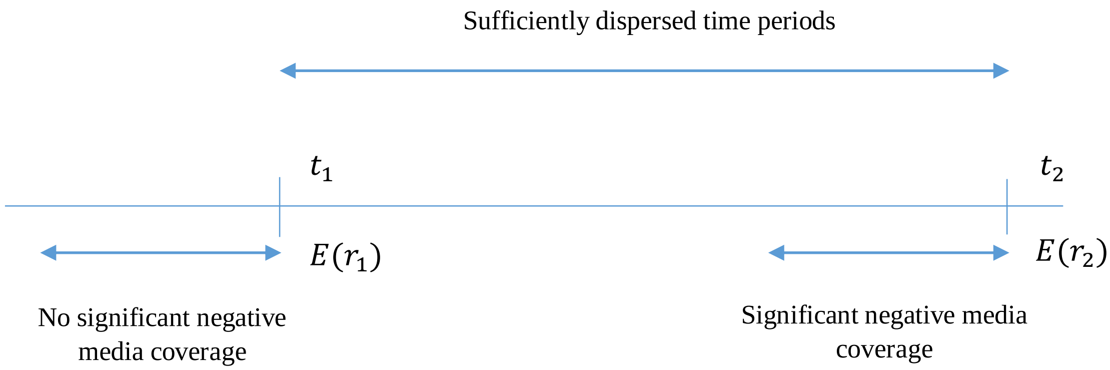
[13] Equation 5 of Goel and Thakor (2014) presents the objective function that relies on an economic micro-foundation.

[14] We consider overall firm quality instead of project quality because the firm level credit rating considers firm quality as a whole.

in two sufficiently dispersed time periods, t_1 and t_2. Before time t_1 the firm attracts no major negative news. During the period before t_2, a substantial level of negative media coverage occurs. Figure A1 presents the scenarios.

Figure A1. A Firm Experiencing Different Media Coverage in Two Periods

This figure describes two sufficiently dispersed time periods t_1 and t_2 that experience different levels of negative media coverage. $E(r_1)$ and $E(r_2)$ denote corresponding rating levels.



The terms $E(r_1)$ and $E(r_2)$ represent the equilibrium credit ratings assigned by a CRA in t_1 and t_2, respectively. We assume that in both periods, t_1 and t_2, a CRA would assign appropriate ratings that maximize its objective function as presented in equation A1. In period t_1, given no major negative media coverage, the equilibrium rating $E(r_1)$ is achieved considering the non-media related determinants of a credit rating as discussed in Section II(A). However, the dynamics change in period t_2. As the firm experiences negative media coverage before period t_2, a CRA is likely to note this firm-specific negative market sentiment for the sake of preserving its reputational capital.

To maximize the social value of a rating (i.e., the first of the two components in the objective function), a CRA has to make a reasonable attempt to integrate the new market sentiment while assigning a credit rating score so that it can uphold its reputation for credible signaling. Failing to do so, a CRA might hurt its chances to increase fees in the subsequent periods and could lose prospective clients (Goel and Thakor, 2015), prompting a CRA to revise its credit rating score downward. Thus, $E(r_2)$ is lower than $E(r_1)$.[15]

[15] Here we assume that a higher rating reflects better firm quality and creditworthiness.

Appendix B. The Rating Scale

The following table describes both credit rating categories and the numerical scale used in this study. Multiple numerical values for a single rating level represent the number assigned to ratings with a + qualifier, no qualifier, and a – qualifier. The Compustat S&P credit rating database serves as the source of the firm level credit rating. Mergent FISD is the source of the bond level credit rating from multiple CRAs.

Rating Group	**Rating Agency**		**Numerical Value Assigned**
	Moody's	**S&P and Fitch**	
Investment Grade	AAA	AAA	2
	Aa(+/–)	AA(+/–)	4,5,6
	A(+/–)	A(+/–)	7,8,9
	Baa(+/–)	BBB(+/–)	10,11,12
Non-Investment Grade	Ba(+/–)	BB(+/–)	13,14,15
	B(+/–)	B(+/–)	16,17,18
	Caa(+/–)	CCC(+/–)	19,20,21
	Ca(+/–)	CC(+/–)	23
	C(+/–)	C(+/–)	25
Default	D	SD/D	27

Appendix C. Variable Descriptions

This table presents the description of all variables used in the study.

Dependent Variables	Calculation Methods	Source (Variable Name)
Panel C.1. Dependent variables		
ChgRating (Firm Level)	Quarterly change of the firm level S&P credit rating, which is coded according to Appendix B.	Compustat (splticrm)
ChgRating (Bond Level)	Quarterly change of the bond level average credit rating from three CRAs (S&P, Moody's, and Fitch), which is coded according to Appendix B.	Mergent FISD (rating)
Yield (Bond) Spread	Logarithm of the bond spread over the benchmark, which is the yield for the government bond with the closest maturity (disregarding the timing of coupon payments). The Federal Reserve's H15 reports are the source of the benchmarks.	Mergent FISD (Flat_price, accrued_Interest, coupon, maturity, and interest_ frequency)
Panel C.2. Media variables		
Negative words ratio (Neg News)	The percentage of negative words out of the total words used in all newspaper articles in the quarter before the credit rating change event. Newswire articles are combined into a single article and then the total number of words and the negative words are counted separately. The positive words ratio (Pos News) is calculated in a similar manner.	Factiva and Loughran and McDonald (2011)
Total negative articles count	The number of negative newspaper articles in the quarter before the credit rating change event. To determine the tone of a negative or positive newspaper article, we compare the number of negative and positive word in an article. If the number of negative words is greater than the number of positive words, we categorize it as a negatively-toned article.	Factiva and Loughran and McDonald (2011)
Negative articles ratio	The percentage of negative newspaper articles out of the total newspaper articles in the quarter before the credit rating change event. To determine the tone of a negative or positive newspaper article, we compare the number of negative and positive words in an article. If the number of negative words is greater than the number of positive words, we categorize it as a negatively-toned article.	Factiva and Loughran and McDonald (2011)
Panel C.3. Other control variables		
Rating Score	Quarter-end rating scores from S&P for the firm level regressions and quarter-end average rating score for the bond level regressions.	Compustat (splticrm) and Mergent FISD (rating)
SIZE	Logarithm of total assets.	Compustat Quarterly (atq)
Leverage (LEV)	Total debt (including short-term debt and liabilities) over total assets (and its square and quarterly change).	Compustat Quarterly (dlttq+dlcq)
Long-term Debt/Total Assets	Long-term debt over total assets.	Compustat Quarterly (dlttq)
Operating Income/ Total Assets	Operating income divided by total assets (and its square and quarterly change).	Compustat Quarterly (oibdpq)
EBITDA/Total Assets	EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by total assets (and its square and quarterly change).	Compustat Annual (ebitda)
Interest Expense/ EBITDA	Interest expense over EBITDA (and its square and quarterly change).	Compustat Annual (oiadp+xint)

Pre-tax Interest Coverage	Pre-tax interest coverage	Compustat Quarterly ((oiadpq+xintq)/xintq)
MTB	Market-to-book value.	Compustat Annual (csho*prcc_f+pstkl+dltt+dlc-txditc)/at
TANG	Net PPE (property, plant, and equipment) divided by total assets (and its square and quarterly change).	Compustat Quarterly (ppentq/atq)
Cash	Cash divided by total assets (and its square and quarterly change).	Compustat Quarterly (cheq/atq)
Cash Flow	Cash flow divided by assets (and its square and quarterly change).	Compustat Quarterly (oancf/atq)
Log(Analysts)	Logarithm of the total number of analysts following the firm for a year.	I/B/E/S (numest)
Beta	Beta of the market model using the value weighted CRSP market index return as a proxy for market returns.	CRSP Daily (ret)
STD(Residue)	Square of the market model residues (idiosyncratic risk).	CRSP Daily (ret)
Log(Maturity)	Logarithm of bond maturity (measured in years).	Mergent FISD (maturity)
Log(Issue-Size)	Logarithm of bond issue size.	Mergent FISD (offering_amt)
Panel C.4. Instrumental variables		
Media Expert	If the CEO or a board member ever has been an employee of a television, radio or newspaper company (with three-digit SIC = 271, 271 or 483). We use three variations of media expert variable and create relevant dummy variables. Media_expert1 is equal to one if any of the board members or the CEO is considered as the media expert as stated above. Media_expert2 is equal to one if any of the board members is a media expert; and Media_expert3 is equal to one if the CEO is a media expert.	Proxy statement of the acquiring firms, annual report, Factiva, and web search.

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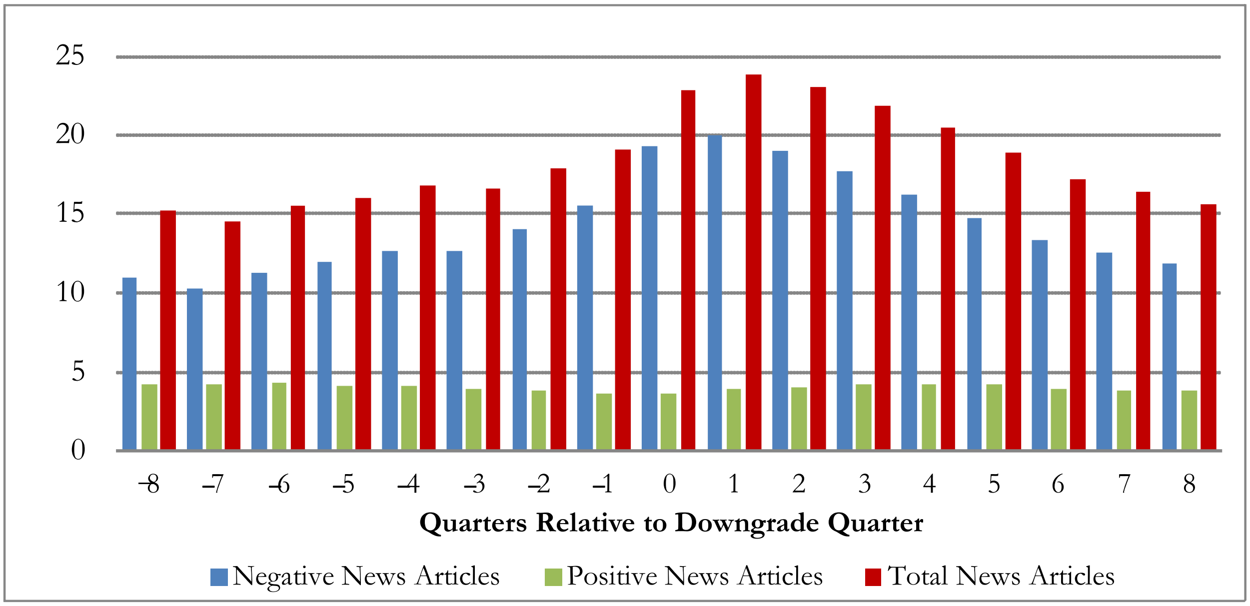
Figure 1. Media Coverage before Rating Changes

This figure shows the number of negative, positive, and total news articles, as shown on the y axis, around the time when firms experience a rating downgrade (Panel A) and a rating upgrade (Panel B). Determining a newspaper article's negative or positive tone involves comparing the number of negative and positive words in an article. If the number of negative words exceeds the number of positive words, we classify it as a negatively-toned article.

Panel A. Media coverage before rating downgrades



Panel B. Media coverage before rating upgrades

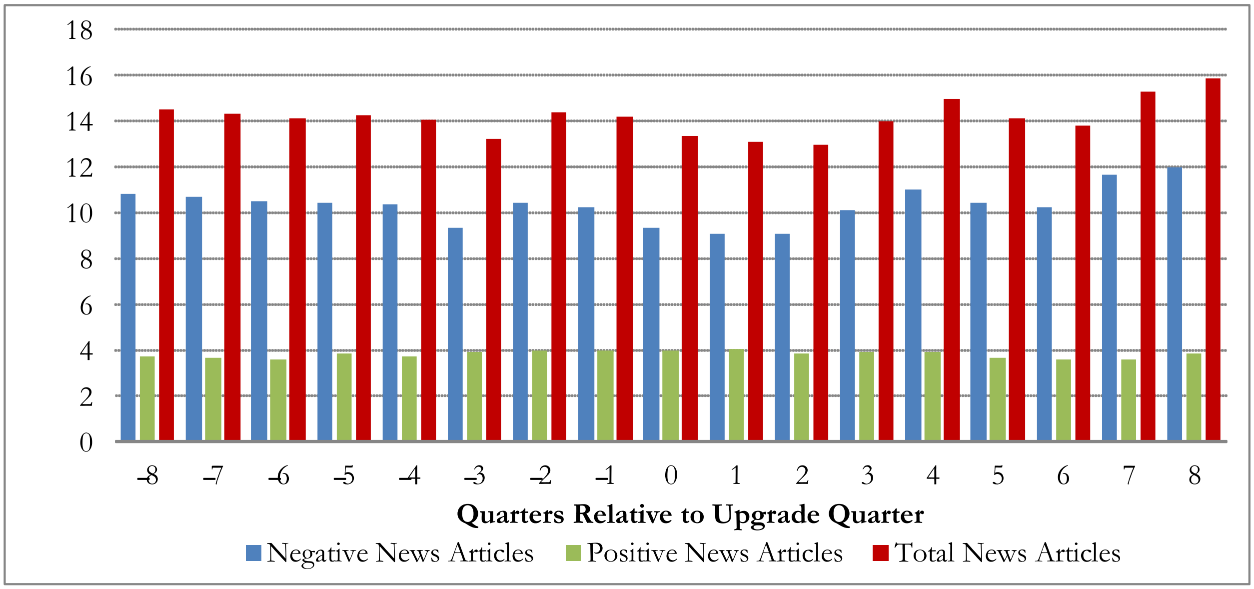


Table 1. Summary Statistics of the Variables Used in the Study

This table shows summary statistics for the variables used in the study as described in Appendix C.

Panel A. Key variables

	Firm Rating	Rating Change	Total Assets ($MM)	Number of Negative News Articles	Negative Words Ratio	Negative Articles Ratio	Number of Positive News Articles	Positive Words Ratio	Positive Articles Ratio
N	69,115	67,853	69,115	69,115	69,115	69,115	69,115	69,115	69,115
Mean	11.6854	0.0235	10,114.88	4.3453	0.0089	0.3355	1.7018	0.0038	0.1539
Median	11.0000	0.0000	3,329.46	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SD	3.6250	0.6868	21,534.79	13.8206	0.0118	0.4118	5.3172	0.0051	0.2773
P25	9.0000	0.0000	1,452.41	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P75	14.0000	0.0000	9,459.85	2.0000	0.0163	0.7500	1.0000	0.0076	0.2500

Panel B. Other firm level control variables

	Sales ($MM)	Leverage	Operating Income/ Total Assets	EBITDA/ Total Assets	Interest/ EBITDA
N	69,115	69,110	69,017	69,085	68,906
Mean	1,866.79	0.3222	0.1599	0.1338	0.8661
Median	725.14	0.3072	0.1417	0.1274	0.8735
SD	2,975.12	0.1722	0.1549	0.0742	0.3546
P25	322.80	0.2061	0.0770	0.0913	0.7631
P75	1,985.60	0.4114	0.2286	0.1721	0.9688

Panel B. Other firm level control variables - continued

	Net PPE/ Total Assets	Cash/ Total Assets	Cash Flow/ Total Assets	MTB	# of Analysts	Beta	STD (Residue)
N	69,110	69,110	69,110	67,403	69,115	48,658	48,658
Mean	0.3608	0.0750	0.0448	1.3025	8.0835	0.9479	0.0219
Median	0.3093	0.0371	0.0364	1.0123	6.0000	0.8810	0.0186
SD	0.2389	0.0999	0.0605	0.9554	9.0018	0.5220	0.0127
P25	0.1614	0.0138	0.0069	0.7517	0.0000	0.5904	0.0138
P75	0.5541	0.0963	0.0761	1.5227	14.0000	1.2206	0.0261

Table 2. Media Coverage and the Change of the Firm Level Credit Rating

This table presents the OLS estimation of the impact of the negative news ratio on a firm's credit rating change (Panel A) and the impact of positive news ratio on a firm's credit rating change (Panel B). The sample period is between 1990 and 2009. The dependent variable is the quarterly change of the firm level S&P credit rating and is coded according to Appendix B. Lag (Neg News) (Lag (Pos News)) is the one-quarter lagged negative news ratio (positive news ratio) coverage in the media. Following Becker and Milbourn (2011), we use control variables in the regression models. As Models 3, 4, and 5 show, firm level controls are divided into two types. First, quarterly control comprises the credit rating score, log of total assets (and its quarterly change), cash divided by total assets (and its square and quarterly change), cash flow divided by assets (and its square and quarterly change), net PPE (property, plant and equipment) divided by total assets (and its square and quarterly change), and debt over total assets (and its square and quarterly change), all measured at the previous fiscal quarter end. Second, yearly controls include market-to-book value, EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by total assets (and its square), and interest expense over EBITDA (and its square). Industry classification is based on the first two digits of the SIC-code from Compustat. Following Becker and Milbourn (2011) standard errors are clustered by industry times the quarter cell to account for the correlations within an industry for a particular quarter. Appendix C provides a description of all variables. ***, **, * indicate significance at 0.01, 0.05, and 0.10 levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Variables	**ChgRating**	**ChgRating**	**ChgRating**	**ChgRating**	**ChgRating**
Panel A. Negative media coverage and the change of the firm-level credit rating					
Lag(Neg News)	2.251***	1.936***	2.739***	2.504***	2.352***
	(5.87)	(5.21)	(7.44)	(6.88)	(6.28)
Rating			–0.051***	–0.053***	–0.114***
			(–8.95)	(–9.25)	(–9.74)
Lag(SIZE)			–0.057***	–0.056***	–0.087***
			(–7.90)	(–7.82)	(–5.52)
Lag(LEV)			0.607***	0.313**	0.319
			(9.82)	(2.50)	(1.62)
Lag(EBITDA/Total Assets)			–0.900***	–1.188***	–1.480***
			(–8.01)	(–7.15)	(–7.55)
Lag(Interest Expense/EBITDA)			–0.044***	–0.098***	–0.062***
			(–2.97)	(–4.51)	(–2.67)
Lag(TANG)			0.047	0.239***	0.472***
			(1.64)	(3.33)	(2.90)
Lag(CASH)			0.072	0.096	–0.022
			(1.64)	(1.14)	(–0.17)
Lag(CASH FLOW)			–0.461***	–0.902***	–0.888***
			(–5.37)	(–7.14)	(–5.83)
Lag(MTB)			–0.031***	–0.043***	–0.029***
			(–6.61)	(–8.33)	(–4.65)
SQ(EBITDA/Total Assets)				1.648***	1.015**
				(3.77)	(2.01)
SQ(Interest Expense/EBITDA)				0.030***	0.021*
				(2.93)	(1.75)
SQ(CASH)				–0.115	–0.135
				(–0.85)	(–0.65)
SQ(CFLOW)				0.989	0.535

				(1.32)	(0.64)
SQ(TANG)				–0.205***	–0.357**
				(–2.85)	(–2.19)
SQ(LEV)				0.307**	0.746***
				(2.07)	(3.18)
Delta(SIZE)				0.027	0.035
				(0.20)	(0.26)
Delta(LEV)				–0.711*	–0.666
				(–1.74)	(–1.62)
Delta(TANG)				0.793	0.840*
				(1.55)	(1.67)
Delta(CASH)				0.545**	0.511**
				(2.37)	(2.29)
Delta(CFLOW)				–0.562***	–0.596***
				(–3.38)	(–3.52)
Constant	0.003	0.059	1.655***	1.735***	3.903***
	(0.93)	(0.88)	(7.53)	(7.95)	(8.07)
Observations	67,853	67,853	66,100	66,100	66,100
R^2	0.002	0.011	0.049	0.055	0.103
YR-Q Fixed	No	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes	No
Firm Fixed	No	No	No	No	Yes

Panel B. Positive media coverage and the change of the firm-level credit rating

Lag(Pos News)	0.602	–0.449	0.624	0.280	–0.448
	(1.08)	(–0.82)	(1.05)	(0.48)	(–0.72)
Rating			–0.050***	–0.052***	–0.114***
			(–8.76)	(–9.09)	(–9.67)
Lag(SIZE)			–0.048***	–0.047***	–0.080***
			(–6.47)	(–6.42)	(–5.06)
Other Firm Controls	Yes	Yes	Yes	Yes	Yes
Observations	67,853	67,853	66,100	66,100	66,100
R^2	0.000	0.010	0.047	0.053	0.102
YR-Q Fixed	No	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes	No
Firm Fixed	No	No	No	No	Yes

Table 3. Testing for Reverse Causality

This table presents the two-stage least square regression results (2SLS) to address the potential reverse causality induced endogeneity bias. Columns (1)-(3) report the results for the first stage regressions and Columns (4)-(6) present the second stage results. Following Gurun (2015) and Liu and McConnell (2013), we use media expert as an instrument for the negative media coverage variable (i.e., Neg News). Media expert is a dummy variable that takes the value of one if the CEO or the board members have or had an association with the media industry. We use three variations of media expert in our analysis. Media_expert1 is equal to one if any of the board members or the CEO is considered as the media expert as stated above. Media_expert2 is equal to one if any of the board members is a media expert; and Media_expert3 is equal to one if the CEO is a media expert. In the first stage regression, we use the negative word ratio (Neg News) as the dependent variable; whereas in the second stage, we use the predicted values of Neg News as obtained from the first stage regression analysis. All the other variables are the same as in Table 2. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	First stage regression			**Second stage regression**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	**Neg News**	**Neg News**	**Neg News**	**ChgRating**	**ChgRating**	**ChgRating**
Media_expert1	−0.001***					
	(−4.67)					
Predicted Neg News (using Media_expert1)				68.504***		
				(2.63)		
Media_expert2		−0.001***				
		(–3.96)				
Predicted Neg News (using Media_expert2)					86.443***	
					(2.91)	
Media_expert3			−0.002***			
			(−5.05)			
Predicted Neg News (using Media_expert3)						52.050**
						(1.99)
Rating	0.000***	0.000***	0.000***	−0.071***	−0.077***	−0.065***
	(10.14)	(10.36)	(10.45)	(−5.29)	(−5.24)	(−5.07)
Lag(SIZE)	0.001***	0.001***	0.001***	−0.091***	−0.103***	−0.081***
	(9.24)	(9.06)	(9.16)	(−4.10)	(−4.19)	(−3.68)
Lag(LEV)	−0.001	−0.001	−0.001	0.339**	0.359**	0.315*
	(−0.72)	(−0.70)	(−0.67)	(1.99)	(2.08)	(1.87)
Lag(EBITDA/Total Assets)	−0.013***	−0.013***	−0.013***	−0.091	0.088	−0.252
	(−6.85)	(−6.82)	(−6.83)	(−0.37)	(0.32)	(−0.99)
Lag(Interest Expense/EBITDA)	−0.000	−0.000	−0.000	−0.131***	−0.128***	−0.135***
	(−0.48)	(−0.48)	(−0.32)	(−3.77)	(−3.65)	(−3.89)
Lag(TANG)	0.004***	0.005***	0.004***	−0.217	−0.303*	−0.139
	(3.21)	(3.25)	(2.95)	(−1.32)	(−1.65)	(−0.89)
Lag(CASH)	0.007***	0.006***	0.006***	−0.198	−0.296	−0.097
	(3.41)	(3.31)	(3.17)	(−0.97)	(−1.38)	(−0.48)
Lag(CASH FLOW)	−0.004**	−0.004**	−0.004*	−0.477**	−0.398	−0.560**
	(−1.98)	(−1.99)	(−1.68)	(−2.03)	(−1.63)	(−2.50)
Lag(MTB)	−0.000	−0.000	−0.000	−0.036***	−0.034***	−0.038***
	(−1.19)	(−1.12)	(−0.97)	(−4.12)	(−3.95)	(−4.50)
SQ(EBITDA/Total Assets)	0.031***	0.031***	0.030***	−0.105	−0.523	0.272
	(5.35)	(5.36)	(5.12)	(−0.13)	(−0.59)	(0.35)
SQ(Interest Expense/EBITDA)	0.000	0.000	0.000	0.038**	0.037**	0.039***
	(0.30)	(0.30)	(0.18)	(2.53)	(2.45)	(2.65)
SQ(CASH)	−0.015***	−0.015***	−0.015***	0.741*	0.973**	0.518

	(−4.34)	(−4.25)	(−4.19)	(1.67)	(2.04)	(1.17)
SQ(CFLOW)	0.002	0.002	−0.000	0.240	0.192	0.311
	(0.18)	(0.16)	(−0.02)	(0.20)	(0.16)	(0.25)
SQ(TANG)	−0.005***	−0.005***	−0.004**	0.211	0.294	0.138
	(−2.68)	(−2.67)	(−2.50)	(1.21)	(1.53)	(0.82)
SQ(LEV)	0.002	0.002	0.002	0.129	0.099	0.164
	(1.02)	(0.94)	(0.95)	(0.54)	(0.41)	(0.69)
Delta(SIZE)	−0.004***	−0.004***	−0.004***	0.313***	0.366***	0.264**
	(−4.99)	(−4.99)	(−4.94)	(2.64)	(3.00)	(2.04)
Delta(LEV)	0.003**	0.003**	0.003**	−1.498**	−1.549**	−1.453**
	(2.05)	(2.02)	(2.04)	(−2.08)	(−2.15)	(−1.97)
Delta(TANG)	−0.001	−0.001	−0.001	1.185**	1.162**	1.198**
	(−0.27)	(−0.24)	(−0.20)	(2.36)	(2.33)	(2.36)
Delta(CASH)	−0.003	−0.003	−0.003	0.901***	0.947***	0.862***
	(−1.08)	(−1.09)	(−1.13)	(2.78)	(2.88)	(2.60)
Delta(CFLOW)	−0.002	−0.003	−0.002	−0.363	−0.320	−0.405
	(−1.33)	(−1.34)	(−1.26)	(–1.22)	(–1.06)	(–1.41)
Constant	−0.000	0.000	−0.000	1.724***	1.719***	1.731***
	(−0.05)	(0.04)	(−0.06)	(6.36)	(6.35)	(6.36)
Observations	17,325	17,325	17,325	17,325	17,325	17,325
R^2	0.047	0.047	0.047	0.057	0.057	0.056
Year-Q Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Testing for the Negative Media Effect with Different Lags

This table presents the results of different lag periods of the impact of negative news on credit rating changes. We use all firm controls in the regression models as in Table 2. For the sake of brevity, we report only the Lag(SIZE) coefficient among the controls. All definitions of the variables are the same as in Table 2. All models are OLS regressions with both year and firm fixed effects. Following Becker and Milbourn (2011), standard errors are clustered by industry times the quarter cell to account for the correlations within an industry for a particular quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)	(4)
Variables	**ChgRating**	**ChgRating**	**ChgRating**	**ChgRating**
Lag2(Neg News)	1.263***			
	(3.07)			
Lag3(Neg News)		0.898**		
		(2.28)		
Lag4(Neg News)			0.805*	
			(1.88)	
Lag5(Neg News)				0.471
				(1.25)
Rating	–0.114***	–0.114***	–0.114***	–0.114***
	(–9.72)	(–9.72)	(–9.71)	(–9.69)
Lag(SIZE)	–0.084***	–0.083***	–0.083***	–0.082***
	(–5.29)	(–5.25)	(–5.21)	(–5.12)
Constant	3.820***	3.798***	3.789***	3.771***
	(7.88)	(7.85)	(7.82)	(7.75)
Other Firm Controls	Yes	Yes	Yes	Yes
Observations	66,100	66,100	66,100	66,100
R^2	0.102	0.102	0.102	0.102
YR-Q Fixed	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes

Table 5. Impact of Negative Media Coverage on Bond Rating Changes

This table presents the impact of negative news on a firm's bond rating change. Bond rating change is measured as the average of all the ratings from different CRAs for estimation in Models 1, 2, 3, 4, and 5. Models 6, 7, and 8 estimate the impact of negative news on S&P, Moody's, and Fitch bond rating changes, respectively. Bond level control variables are: Log (Maturity), which is the logarithm of bond maturity, and Log (Issue-Size), which is the logarithm of bond issuing size. Firm level controls are the same as in Table 2. Following Becker and Milbourn (2011), standard errors are clustered by industry times the quarter cell to account for the correlations within an industry for a particular quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**ChgRating**	**ChgRating**	**ChgRating**	**ChgRating**	**ChgRating**	**S&P**	**Moody's**	**Fitch**
Lag(Neg News)	10.996***	8.673***	9.702***	6.118***	6.116***	13.326***	9.136***	9.256***
	(6.31)	(6.27)	(7.00)	(4.28)	(4.84)	(3.91)	(4.91)	(3.04)
Log(Maturity)			0.005	−0.020**	0.031**	0.054**	0.072***	0.009
			(0.43)	(−2.03)	(2.33)	(2.32)	(2.71)	(0.42)
Log(Issuing Amount)			0.050***	0.060***	0.106***	0.182***	0.046**	−0.057
			(2.75)	(3.46)	(2.88)	(6.39)	(2.25)	(−1.50)
Rating			−0.044***	−0.156***	−0.288***	−0.176**	−0.084**	−0.176***
			(−5.48)	(−10.75)	(−4.53)	(−2.15)	(−2.06)	(−2.79)
Lag(SIZE)				−0.192***	−0.185	−0.350*	0.113	−0.059
				(−8.69)	(−1.45)	(−1.68)	(0.66)	(−0.25)
Lag(LEV)				1.049**	2.486**	2.309	4.424***	-4.900
				(2.35)	(2.58)	(0.61)	(3.09)	(-0.94)
Lag(EBITDA/Total Assets)				−3.031***	−3.449***	−5.394***	−3.437***	−2.059***
				(−6.93)	(−3.37)	(−3.41)	(−4.68)	(−2.77)
Lag(Interest Expense/EBITDA)				0.103	0.302*	0.690	0.061	−0.918**
				(0.70)	(1.86)	(1.60)	(0.52)	(−2.44)
Lag(TANG)				0.660**	0.681	1.071	0.025	0.818
				(2.56)	(0.44)	(0.46)	(0.01)	(0.38)
Lag(CASH)				1.164***	1.344	1.166	2.086	0.732
				(2.68)	(1.55)	(0.86)	(1.54)	(0.42)
Lag(CASH FLOW)				−2.670***	−2.450***	−5.310***	−2.712***	−3.039**
				(−5.47)	(−3.58)	(−3.15)	(−2.98)	(−2.27)
Lag(MTB)				−0.127***	−0.034	−0.000	−0.066	−0.350***
				(−5.67)	(−0.62)	(−0.00)	(−1.15)	(−2.72)
SQ(EBITDA/Total Assets)				2.118*	0.745	−2.932	−1.307	−1.587
				(1.88)	(0.37)	(−0.70)	(−0.55)	(−0.51)
SQ(Interest Expense/EBITDA)				−0.004	−0.069	−0.023	0.002	0.434***
				(−0.08)	(−0.93)	(−0.18)	(0.04)	(3.43)

SQ(CASH)				−2.021**	−2.167	−4.217	−5.034**	−2.405
				(−1.97)	(−1.15)	(−1.63)	(−2.15)	(−0.85)
SQ(CFLOW)				6.766***	10.635**	15.454**	5.443	13.022
				(2.67)	(2.38)	(2.08)	(1.29)	(1.55)
SQ(TANG)				−0.689**	−0.566	−3.380	−1.626	−1.303
				(−2.31)	(−0.40)	(−1.23)	(−0.91)	(−0.63)
SQ(LEV)				1.493***	1.853	2.061	−0.955	7.812
				(2.84)	(1.40)	(0.64)	(−0.69)	(1.52)
Delta(SIZE)				−0.692***	−0.697***	−0.476**	−0.286**	−0.119
				(−3.86)	(−2.73)	(−2.43)	(−2.11)	(−0.51)
Delta(LEV)				1.813***	2.295***	2.017**	1.952***	1.329
				(3.02)	(4.32)	(2.08)	(5.25)	(1.37)
Delta(TANG)				−0.297	−0.191	−3.101***	−2.181***	−0.008
				(−0.34)	(−0.23)	(−2.74)	(−3.75)	(−0.01)
Delta(CASH)				1.139**	1.011**	0.550	0.988**	0.830
				(2.30)	(2.23)	(0.89)	(2.00)	(1.38)
Delta(CFLOW)				−0.850*	−0.360	−1.166***	−1.092***	−0.210
				(−1.93)	(−1.47)	(−3.05)	(−3.12)	(−0.44)
Observations	84,536	84,536	84,452	84,073	84,073	74,648	65,319	41,574
R^2	0.008	0.051	0.064	0.149	0.192	0.284	0.231	0.154
YR-Q Fixed	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes	No	No	No	No
Firm Fixed	No	No	No	No	Yes	Yes	Yes	Yes

Table 6. Impact of Negative Media Coverage on Bond Spreads

This table presents the impact of negative news on bond spreads. Bond spread is a corporate bond's YTM minus a government bond's YTM with the closest maturity. Log (Maturity) is the logarithm of bond maturity. Log (Issue-Size) is the logarithm of the bond issuing size. Rating is the bond average credit rating from all three CRAs: S&P, Moody's, and Fitch. Other control variables include lagged long-term debt divided by total assets, Lag (Long-term Debt/Total Assets), lagged operating income divided by total assets, Lag(Operating Income/Total Assets), lagged pre-tax interest coverage (pre-tax interest coverage), logarithm of one plus the number of analysts following the firm, Log (Analysts), systematic risk (Beta), and idiosyncratic risk (STD (Residue)) estimated from the market model using the CRSP daily price. The definitions of the other control variables are the same as in Table 2. Following Becker and Milbourn (2011), standard errors are clustered by industry times the quarter cell to account for the correlations within an industry for a particular quarter. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)
Variables	**Bond Spread**	**Bond Spread**	**Bond Spread**
Lag(Neg News)	0.2848***	0.0894***	0.1009***
	(5.64)	(3.59)	(3.44)
Rating	0.0040***	0.0011***	0.0007***
	(22.71)	(9.77)	(6.06)
Log(Maturity)		0.0013***	–0.0011
		(3.64)	(–0.36)
Log(Issue-Size)		–0.0023**	
		(–2.56)	
Lag(Size)		0.0005	–0.0045*
		(0.88)	(–1.70)
Lag(Long-term Debt/Total Assets)		0.0144***	0.0135
		(3.25)	(1.42)
Lag(LEV)		0.0234***	0.0376**
		(5.41)	(2.61)
Lag(Operating Income/Total Assets)		–0.0152***	–0.0179***
		(–5.10)	(–3.29)
Lag(Pre-tax Interest Coverage)		0.0000**	–0.0000
		(2.46)	(–0.74)
Lag(TANG)		0.0059**	0.0089
		(2.55)	(0.87)
Lag(Cash)		0.0064	0.0001
		(1.10)	(0.01)
Lag(Cash Flow)		–0.0106	0.0021
		(–1.15)	(0.17)
Lag(MTB)		–0.0009**	–0.0025**
		(–2.07)	(–2.29)
Log(analysts)		–0.0025***	0.0005
		(–4.43)	(0.71)
Beta		0.0031***	0.0044**
		(3.00)	(2.13)
STD(Residue)		1.2007***	1.1234***
		(10.83)	(6.16)
Observations	195,635	167,397	167,397
R^2	0.460	0.620	0.453
YR-Q Fixed and Industry Fixed	Yes	Yes	Yes
Issue Fixed	No	No	Yes

Table 7. Ordered Probit Model and Panel Regression

This table presents the ordered probit model regression and panel regression results of the impact of negative news on the firm level credit rating changes. All variables are the same as in Table 2. Models 1 and 2 present the ordered probit models in which the standard errors are clustered by industry times the quarter cell to account for the correlations within an industry for a particular quarter. Models 3 and 4 are the panel regression models in which the standard errors are estimated with clustering at the firm dimension. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

	Ordered Probit Model		**Panel Model**	
	(1)	**(2)**	**(3)**	**(4)**
Variables	**ChgRating**	**ChgRating**	**Fixed**	**Radom**
Lag(Neg News)	8.028***	8.461***	2.352***	2.864***
	(11.07)	(11.20)	(6.71)	(8.50)
Rating	–0.121***	–0.220***	–0.114***	–0.044***
	(–26.06)	(–28.91)	(–12.71)	(–9.78)
Lag(SIZE)	–0.111***	–0.095***	–0.087***	–0.051***
	(–11.94)	(–3.84)	(–5.55)	(–8.74)
Other Firm Controls	Yes	Yes	Yes	Yes
Observations	66,100	66,100	66,100	66,100
R^2			0.085	
YR-Q Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	No	No	No
Firm Fixed	No	Yes	Yes	No

Table 8. Firm Level Credit Rating: Various Robustness Tests

This table presents the robustness test results of the impact of negative news on credit rating changes using different measures of negative news coverage (Panel A), different clustering methods (Panel B), and different sub-samples (Panel C). We use all firm controls in the regression models as in Table 2. For the sake of brevity, we report only the Lag(SIZE) coefficient among the controls. All the definition of the variables is the same as in Table 2. The first two columns of Panel A present the results of using the negative articles ratio as the media coverage metric and the last two columns of Panel A presents the results with total negative articles counts as the media coverage metric. Models 1 and 3 in Panel A are OLS estimation and Model 2 and 4 in Panel A are ordered probit model specification with standard errors clustered by industry times the quarter cell to account for the correlations within an industry for a particular quarter. Panel B uses the OLS model with standard errors clustered at the firm dimension (Model 1), quarter dimension (Model 2), and two-way clustering at both the firm and quarter dimension (Model 3). Panel C shows the results of different sub-samples with the OLS model and clustered at the industry times the year-quarter dimensions. Model 1 and 2 considers two sample periods; Model 3, 4, and 5 present the results for different ratings; and Models 6, 7, and 8 present the results for different size terciles. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Panel A. Different measures of negative news coverage

	Negative Articles Ratio		**Total Negative Articles Counts**	
	(1)	**(2)**	**(3)**	**(4)**
Variables	**OLS**	**Ordered Probit**	**OLS**	**Ordered Probit**
Lag(Neg News)	0.049***	0.214***	0.004***	0.009***
	(5.00)	(9.07)	(4.72)	(7.68)
Rating	–0.114***	–0.219***	–0.114***	–0.220***
	(–9.70)	(–28.72)	(–9.76)	(–28.81)
Lag(SIZE)	–0.085***	–0.091***	–0.089***	–0.092***
	(–5.42)	(–3.69)	(–5.56)	(–3.72)
Other Firm Controls	Yes	Yes	Yes	Yes
Observations	66,100	66,100	66,100	66,100
R^2	0.103		0.104	
YR-Q Fixed	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes

Panel B. Different clustering methods

Variables	(1) Cluster at Firm Dimension	(2) Cluster at Quarter Dimension	(3) Two Way Clustering
Lag(Neg News)	2.352***	2.352***	2.352***
	(6.65)	(5.59)	(5.50)
Rating	–0.114***	–0.114***	–0.114***
	(–12.60)	(–8.68)	(–9.99)
Lag(SIZE)	–0.087***	–0.087***	–0.087***
	(–5.50)	(–5.18)	(–4.88)
Other Firm Controls	Yes	Yes	Yes
Observations	66,100	66,100	66,100
R^2	0.103	0.103	0.103
YR-Q Fixed	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes

Panel C. Various sub-samples

Variables	(1) 1990 to 1999	(2) 2000 to 2009	(3) Investment Grade	(4) Speculative Grade	(5) IG to SG	(6) Small Size	(7) Medium Size	(8) Large Size
Lag(Neg News)	1.061***	2.751***	1.549***	3.158***	0.188***	1.760***	2.513***	2.589***
	(2.79)	(5.00)	(5.37)	(4.02)	(4.48)	(2.91)	(3.75)	(4.23)
Rating	–0.119***	–0.167***	–0.054***	–0.190***	−0.003***	–0.154***	–0.129***	–0.120***
	(–9.49)	(–8.97)	(–12.67)	(–8.09)	(−9.42)	(–5.80)	(–5.89)	(–5.62)
Lag(SIZE)	–0.095***	–0.102***	–0.020**	–0.131***	−0.001	–0.200***	–0.110**	–0.067***
	(–5.17)	(–3.21)	(–2.35)	(–4.49)	(−1.11)	(–4.82)	(–2.28)	(–2.66)
Other Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,594	42,506	40,879	25,221	66,100	21,475	22,254	22,371
R^2	0.117	0.147	0.096	0.177	0.026	0.164	0.155	0.138
YR-Q Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Bond Level Rating: Various Robustness Tests

This table presents the robustness test results of the impact of negative news on bond average credit rating changes using different measures of negative news coverage (Panel A), different clustering methods (Panel B), and different sub-samples (Panel C). All control variables are the same as in Table 2. For the sake of brevity, we report only the Lag(SIZE) coefficient among the controls. The first two columns of Panel A present the results of using the negative articles ratio as the media coverage metric and the last two columns of Panel A presents the results with total negative articles counts as the media coverage metric. Models 1 and 3 in Panel A are OLS estimation and Models 2 and 4 in Panel A are ordered probit model specification with standard errors clustered at the industry times year-quarter dimensions. Panel B uses the OLS model with standard errors clustered at the firm dimension (Model 1), quarter dimension (Model 2), and two-way clustering at both the firm and quarter dimension (Model 3). Panel C shows the results of different sub-samples with the OLS model and clustered at the industry times the year-quarter dimensions. Models 1 and 2 consider two sample periods, Models 3, 4, and 5 present the results for different ratings and Models 6, 7, and 8 present results for different size terciles. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, respectively.

Panel A. Different measures of negative news coverage

	Negative Articles Ratio		Total Negative Articles Counts	
	(1)	(2)	(3)	(4)
Variables	**OLS**	**Ordered Probit**	**OLS**	**Ordered Probit**
Lag(Neg News)	0.193***	0.223***	0.004***	0.006***
	(5.29)	(5.68)	(2.74)	(4.26)
Rating	−0.153***	−0.152***	−0.154***	−0.153***
	(−10.75)	(-18.97)	(−10.81)	(−19.18)
Lag(SIZE)	−0.176***	−0.173***	−0.225***	−0.242***
	(−8.48)	(-10.37)	(−9.16)	(−10.29)
Other Firm Controls	Yes	Yes	Yes	Yes
Observations	84,157	84,157	84,157	84,157
R^2	0.146		0.147	
YR-Q Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes

Panel B. Different clustering methods

Variables	(1) Cluster at Firm Dimension	(2) Cluster at Quarter Dimension	(3) Two Way Clustering
Lag(Neg News)	6.135***	6.135***	6.135***
	(4.82)	(3.63)	(3.95)
Rating	−0.154***	−0.154***	−0.154***
	(−4.66)	(−10.64)	(−4.64)
Lag(SIZE)	−0.177***	−0.177***	−0.177***
	(−4.16)	(−9.49)	(−4.25)
Other Firm Controls	Yes	Yes	Yes
Observations	84,157	84,157	84,157
R^2	0.147	0.147	0.147
YR-Q Fixed	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes

Panel C. Various sub-samples

Variables	(1) 1990 to 1999	(2) 2000 to 2009	(3) Investment Grade	(4) Speculative Grade	(5) IG to SG	(6) Small Size	(7) Medium Size	(8) Large Size
Lag(Neg News)	3.324*	5.618***	5.990***	4.802**	0.648***	5.599***	5.941***	9.690***
	(1.92)	(3.30)	(4.03)	(1.98)	(3.10)	(4.78)	(3.33)	(3.05)
Rating	−0.185***	−0.165***	−0.142***	−0.210***	−0.011***	−0.142***	−0.212***	−0.289***
	(−13.18)	(−9.85)	(−19.35)	(−5.21)	(−4.26)	(−18.86)	(−11.33)	(−5.49)
Lag(SIZE)	−0.150***	−0.191***	−0.136***	−0.206***	−0.015***	−0.131***	−0.331***	−0.347***
	(−5.69)	(−7.93)	(−9.52)	(−4.73)	(−5.11)	(−4.45)	(−3.35)	(−3.44)
Other Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,257	64,900	64,360	18,843	84,188	27,905	28,165	28,087
R^2	0.217	0.153	0.243	0.232	0.179	0.171	0.222	0.261
YR-Q Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes