Management Science

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Sumit Agarwal, Vincent Y. S. Chen, Weina Zhang

MANAGEMENT SCIENCE
Vol. 62, No. 8, August 2016, pp. 2218–2240
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2015.2243

The Information Value of Credit Rating Action Reports: A Textual Analysis

Sumit Agarwal
NUS Business School, National University of Singapore, Singapore 119245, bizagarw@nus.edu.sg

Vincent Y. S. Chen
Department of Accounting, National Chengchi University, Taiwan 11605; and Department of Accounting, National University of Singapore, Singapore 119245, vyschen@nccu.edu.tw

Weina Zhang
NUS Business School, National University of Singapore, Singapore 119245, weina@nus.edu.sg

We examine whether Standard & Poor's (S&P) *credit rating action reports* contain new default-related information beyond credit rating actions such as rating changes, credit watch, and outlooks. We find that the net linguistic tone (negative minus positive tone) in the reports is significantly and negatively related to abnormal returns and predicts future rating changes. We discover that the provision of tone does not seem to be inflated by the conventional proxies of conflict of interest faced by S&P, as higher conflict of interest is related to more negative net tone. Moreover, the tone can predict future rating changes even when conflict of interest is high. Overall, our study reveals novel evidence on the information value of credit rating action reports.

Keywords: credit ratings; credit rating agencies; credit rating action reports; linguistic tone
History: Received March 7, 2014; accepted April 26, 2015, by Wei Jiang, finance. Published online in *Articles in Advance* January 8, 2016.

1. Introduction

Credit rating agencies (CRAs) are known to provide credit rating services for firms. Although there is a huge literature on the information value of the rating actions,[1] there is no study that examines the credit rating action reports that are released concurrently with the credit rating actions by CRAs. Our paper fills this void.

Studying the information contents of credit rating action reports is useful for several reasons. First, credit ratings are discrete measures of the creditworthiness of the rated firm, whereas the firm's default risk can be continuous. The rating action reports may contain detailed default-related information that has been overlooked by the prior literature. Second, CRAs have been criticized for providing inflated credit ratings due to the conflict of interest.[2] As a result, the regulators have proposed and implemented various rules to increase the transparency of credit ratings and enhance the accountability of CRAs. Moreover, in accordance with the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010, the Securities Exchange Commission (SEC) has proposed to regulate the format and content of credit rating action reports. A better understanding of the reports would assist both investors and regulators to make more informed decisions.

The credit rating action reports are downloaded from the Standard & Poor's (S&P) RatingsDirect database, from 1998 to 2010. After merging the rating action reports with the data from Center for Research in Security Prices (CRSP) and Compustat, we have 3,046 usable reports that were released concurrently with credit rating actions. To quantify the information content of each rating report, we classify the positive and negative words used in each report according to Loughran and McDonald's (2011) word list and compute the positive and negative tone as the ratio of these words to the total number of words in the report. We then compute the net tone, measured as negative tone minus positive tone, to quantify the overall tone in the report. A higher net tone implies a more negative overall tone in the report.

Our first testable hypothesis centers on the novel information value of the tone contained in credit rating action reports. We find that the net tone is significantly and negatively related to abnormal stock returns after controlling for various rating actions such as rating changes, credit watch, and rating outlooks. The economic impact of the tone is significant:

[1] For example, Holthausen and Leftwich (1986), Hand et al. (1992), and Dichev and Piotroski (2001) investigate the information value of credit rating actions on stock and bond returns using different samples.

[2] For example, He et al. (2012), Griffin and Tang (2012), Mählmann (2011), and Jiang et al. (2012) have documented rating inflation in structured credit products as well as traditional corporate ratings.

a one-standard-deviation increase in net tone leads to −1.10% in the three-day cumulative abnormal return (*CAR*). Compared to −2.29% in the three-day *CAR* during a rating downgrade, the effect of the tone on the return is about half of that of a downgrade. A closer examination of the net tone reveals that most of the information value comes from the negative tone rather than the positive tone. We also find that the net tone predicts future rating downgrades in one-year and two-year horizons. The predictability of the tone for future rating downgrades serves as a confirmation that tone contains default-related information.

Given that tone contains new valuable information, we ponder whether the provision of the tone suffers from the same fate as credit rating actions, which are subjected to the conflict of interest faced by CRAs due to an issuer-paid rating model. In the rating literature, CRAs are found to inflate credit ratings to cater to the rated firms due to conflict of interest. Since rating fees are collected based on the credit ratings assigned by CRAs rather than the rating reports, it is not clear if the reports also suffer from the same degree of conflict of interest.[3]

Our second empirical hypothesis verifies the link between the provision of tone and the conflict of interest. We employ four empirical measures to proxy for the conflict of interest from the existing literature, which captures the willingness of CRAs to inflate the ratings or to cater to their clients. Specifically, we use the length of S&P's business relation with the rated firm, the outstanding amount of all rated bonds in the firm, the number of the rated bonds, and the increased litigation risk faced by S&P. If the conflict of interest matters in the provision of the tone, we expect that a higher level of conflict of interest will lead to more positive tone. However, our results do not support the conflict of interest hypothesis and show the opposite relation: the conflict of interest proxies are significantly and positively related to the net tone. This result seems to suggest that the conflict of interest does not seem to lead to the inflation of tone. Another way to test the impact of conflict of interest on tone provision is to verify the information content of the tone. Using the future rating changes to proxy for default risk, we find that net tone consistently predicts future rating downgrades regardless of the level of the conflict of interest faced by S&P. This result corroborates with the prior evidence that the tone is not inflated and still carries default-related information even when conflict of interest is high. Hence, these results indicate that rating action reports are not severely affected by the conflict of interest, unlike the provision of credit ratings. Investors and issuers may pay more attention to credit ratings than the contents of the reports because various regulations and rules had adopted credit ratings as references of credit quality before 2009 (e.g., Brown et al. 2015).[4]

We conduct several robustness tests. First, we construct alternative measures of tone by using a statistical approach, a naïve Bayesian algorithm, to mitigate the measurement errors in tone. Second, using the naïve Bayesian approach, we categorize the tone into seven groups of specific information content, such as finance and accounting, management, operation, industry, legal, macroeconomic information, and others. We find that the finance- and accounting-related tone information is most significantly related to abnormal stock returns, and macroeconomic information is mostly significantly related to future rating changes. We also conduct additional tests to eliminate the concern that our results are sensitive to confounding news releases from stock analysts surrounding rating action announcements or to credit rating analysts characteristics. Our two main results are robust.[5]

Our study contributes to the literature in two distinctive ways. First, we are among the first to uncover the information value of credit rating action reports. The prior literature mainly focuses on the information contents of credit rating actions rather than those of the rating reports. Our study employs textual analysis to reveal that rating action reports provide incremental information beyond rating actions and can be used to better assess the default risk in the rated firms.

Second, our study sheds lights on the incentives of CRAs in the provision of the default assessment. In the assignment of credit ratings, the prior literature has documented convincing evidence that the conflict of interest causes CRAs to provide inflated ratings in corporate bonds and structural credit products (e.g., Mählmann 2011, He et al. 2012, Griffin and Tang 2012, Jiang et al. 2012, Kraft 2015). In the context of rating action reports, such incentive does not seem to drive the provision of the tone. Moreover, the information value of these reports is not affected by conflict of interest, unlike credit ratings. Hence, we provide new

[3] S&P does not charge any additional fees for the production and dissemination of the reports in their website or electronic platforms (Standard & Poor's Financial Services 2014).

[4] Related U.S. Securities Exchange Committee (SEC) regulations and rules include the following: Rules 134, 138, 139, 168, 415, 436, forms S-3, S-4, F-1, F-3, F-4, and F-9 under the Securities Act of 1933; Rules 3a1-1, 10b-10, 15c3-1, 15c3-3, Rules 101 and 102 of Regulation M, Regulation ATS, forms ATS-R, PILOT, and X-17A-5 Part IIB under the Securities Exchange Act of 1934; Rules 2a-7, 3a-7, 5b-3, and 10f-3 under the Investment Company Act of 1940 and rule 206(3)-3T under the Investment Advisers Act of 1940. In 2009, the SEC issued a rule that eliminated references to credit ratings in certain rules and forms under the Securities Exchange Act of 1934 and the Investment Company Act of 1940 (U.S. Securities and Exchange Commission 2009).

[5] These results are available upon requests.

evidence supporting the information provisional role of CRAs (e.g., Cantor and Packer 1994, Covitz and Harrison 2003, Bonsall 2014, Xia 2014).

The remainder of this paper is organized as follows. Section 2 presents the institutional background of credit rating action reports and develops empirical hypotheses. Section 3 describes the data and defines key variables. Section 4 reports the empirical findings. Section 5 presents robustness tests. Section 6 concludes.

2. Institutional Background and Hypothesis Development

This section describes the institutional background of credit rating action reports and develops two main empirical hypotheses.

2.1. Institutional Background of Credit Rating Action Reports

A credit rating report typically describes the rationale behind a rating action and is a reflection of accountability of the CRA for the rated company and information users. It is a common industry practice for CRAs to provide credit rating action reports during credit rating action announcements. For example, S&P, in its "Assignment of Credit Ratings'' policy statement, states that S&P generally provides a credit rating rationale with the publication of a rating action. Explicitly, S&P states that "[o]ur recognition as a rating agency ultimately depends on investors' willingness to accept our judgment. We believe it is important that all of our ratings users understand how we arrive at those ratings" (Standard & Poor's Financial Services 2008, p. 3). We provide two sample rating action reports in Appendix A. Similarly, Moody's, in its Policy on Communication of Public Rating Actions in 2013, uses the term "rating announcement'' for written communications to supplement the publication of a credit rating action. In their report of the rating process in 2006, Fitch indicates that a rating commentary will be simultaneously released when a rating action is released to the public. The rating commentary provides a rationale and relevant criteria and methodology applied in the rating process to justify the credit rating action.

Regulators had not regulated the format and content of credit rating reports until the enactment of the Dodd–Frank Act in 2010. To enhance the regulation, accountability, and transparency of nationally recognized statistical rating organizations (NRSROs), Section 932 of the Dodd–Frank Act amends Section 15E of the Securities Exchange Act of 1934, in which the amendment prescribes that the SEC shall require CRAs under the NRSROs to provide a credit rating report to accompany the publication of a credit rating action and regulate the format and content of the credit rating report. Specifically, Section 15E(s)(2) contains the provisions with respect to the format of the report, and Section 15E(s)(3) regulates the quantitative and qualitative information to be included in the content of the report.[6] The SEC issued a paper on May 18, 2011 (U.S. Securities and Exchange Commission 2011), to propose new rules and amendments with respect to the Dodd–Frank Act provisions pertaining to CRAs with an aim to increase the transparency and improve the integrity of credit ratings. The final rules were adopted on August 27, 2014 (U.S. Securities and Exchange Commission 2014). The SEC amended Rule 17g-7 to implement Section 15E(s), effective on June 15, 2015. This newly adopted disclosure regulation does not affect CRAs in our sample period, ending in 2010. However, our study may serve as a pilot study to explore the validity and usefulness of regulating the format and content of credit rating reports.

2.2. Hypothesis Development

We propose two main hypotheses on the information value of tone in credit rating action reports and the incentive of CRAs behind the provision of the tone, respectively.

2.2.1. The Information Value of Tone. The literature has shown that rating actions contained in rating reports are valuable information. For example, Holthausen and Leftwich (1986) find that investors react strongly to downgrades but weakly to upgrades. Using daily bond data, Hand et al. (1992) find significantly negative stock and bond abnormal returns during downgrades and unexpected additions to credit watches. Goh and Ederington (1993) propose that not all downgrades convey new information to the markets and find that the market reacts to downgrades with deteriorating financial prospect and to upgrades with increased leverage. Using a more comprehensive data set, Dichev and Piotroski (2001) report a three-day price effect of −1.97% for downgrades and 0.48% for upgrades. More recent literature mainly focuses on the impact of the regulatory changes on CRAs. For

[6] Section 15E(s)(2) states that the report shall be easy to use and helpful to users, and the dissemination of the report should be made readily available to users in electronic or paper form. Section 15E(s)(3) lists items to be included in the qualitative content, including the credit rating, assumptions and principles used in the rating procedures and methodologies, potential limitations of the credit rating, information about the uncertainty of the credit rating, the engagement of the third-party due diligence, the description of the data used in the procedures or methodologies, an overall assessment of available qualitative information, conflict of interest information, and additional information required by the SEC. Quantitative information required to be disclosed in the credit rating report comprises the potential volatility of the credit rating, the historical performance or expected default probability of the credit rating, sensitivity tests on the assumptions made to form the credit rating, and additional information requested by the SEC.

example, Jorion et al. (2005) examine the information value of credit ratings before and after Regulation Fair Disclosure (Regulation FD) and find that the information value of credit ratings increased after Regulation FD. Using the passage of the Sarbanes–Oxley (SOX) Act on July 25, 2002, as a cutoff point for increased regulatory scrutiny, Cheng and Neamtiu (2009) find that CRAs issued more timely and accurate ratings after the adoption of the SOX Act. Dimitrov et al. (2015) investigate the impact of the Dodd–Frank Act on CRAs and find that CRAs became more conservative in issuing credit ratings, resulting in less informative credit ratings.

Besides rating changes, CRAs also issue other rating actions, such as credit watch and rating outlooks, in the rating reports, and these actions are found to contain valuable information as well. For example, Chung et al. (2012) examine the informational value of credit watch actions issued by Moody's from 2002 to 2010 and find that these actions provide new information to the market. Cantor and Mann (2006) find that rating outlooks predicted default risk and increased the rating accuracy for a sample from 1996 to 2003.

However, there is no empirical study that has examined other information content in credit rating action reports. Since rating action reports also contain the rationale behind rating actions and the CRA's assessment of the default risk in the fine print, such information can be a valuable supplement to discrete rating actions in assessing the underlying firm's default risk. To examine the value of the fine print in the rating reports, we rely on the prior literature that employs linguistic tone to quantify the qualitative information content in documents such as news articles and firms' 10-K filings (e.g., Tetlock 2007, Tetlock et al. 2008, Huang et al. 2013). The literature usually finds that tone contains valuable information for the stock market, and positive (negative) tone is related to positive (negative) returns. Hence, we propose the first hypothesis on the tone of rating action reports as follows:

Hypothesis 1 (The Information Value of Tone). *The linguistic tone in credit rating action reports contains new default-related information beyond rating actions such as credit rating changes, credit watch, and rating outlooks.*

To verify the distinctive information value of the tone, we need to test Hypothesis 1 under three types of rating actions: rating changes, credit watch, and rating outlooks. Credit watch reflects the likelihood in the near future that the rated firm may deviate from expected performance. Rating outlook indicates the potential for future rating changes of the rated firm in the next 6 to 24 months. If rating action reports provide valuable default-related information for investors, tone in the report shall still be strongly related to stock returns after controlling for different types of rating actions since stock returns capture default risk according to the structural model developed by Merton (1974). Alternatively, we may also verify the information content of tone by finding a direct significant link between the tone and the expected default risk. We use future credit rating changes (the realized change of default risk) to proxy for the expected default risk. The significant link between the two will provide more empirical support for Hypothesis 1.

2.2.2. Incentives Behind the Provision of Tone. CRAs are often criticized for facing the conflict of interest originated from an issuer-paid business model (e.g., Financial Crisis Inquiry Commission 2011, Sangiorgi and Spatt 2015). There is ample empirical evidence supporting the argument. For example, He et al. (2012) find that mortgage-backed securities ratings are inflated, and Griffin and Tang (2012) find similar evidence among collateralized debt obligations. Although the corporate credit ratings are usually considered more conservative (Cornaggia and Cornaggia 2013), Mählmann (2011) and Jiang et al. (2012) still find evidence that the inflated corporate credit ratings are related to the length of the business relationship between the CRA and rated firm and the issuer-paid rating fees. Griffin et al. (2013) further show that the conflict of interest can increase as a result of rating shopping behavior by the rated firms. Kraft (2015) also provides evidence of rating catering by Moody's for borrowers with rating-based performance-priced loan contracts. Hence, conflict of interest is a major concern when the public evaluates the CRAs' rating products.

To defend themselves, CRAs often claim that their reputation is of the utmost concern, and they have taken different steps to reduce the conflict of interest (Standard & Poor's Financial Services 2012). The literature has identified and examined several potential channels that may reduce the conflict of interest, such as regulatory scrutiny, competition pressure, and litigation risk. Nevertheless, the literature lacks strong supporting evidence on these disciplinary channels. For example, Kisgen and Strahan (2010) find that the regulation pressure can actually lead to more inflated ratings. Opp et al. (2013) show that the disciplinary role of regulation is limited, and Goel and Thakor (2011) indicate that litigation would discipline CRAs' rating behavior, but may also lead to more downward-biased ratings. Moreover, Skreta and Veldkamp (2009), Becker and Milbourn (2011), Bolton et al. (2012), and Griffin et al. (2013) are among the many that show that competition may even facilitate the rating catering behavior of CRAs.

Overall, the credit rating literature has shown that conflict of interest is a major concern for CRAs. It is likely that the provision of tone in rating action reports may be driven by a similar issue. Hence, we hypothesize that CRAs may give a more favorable tone in reports when the conflict of interest is higher. When this happens, the market may discount the information content of the tone more. These conjectures lead to our second hypothesis, as follows:

Hypothesis 2 (The Incentive of Tone Provision). *More favorable tone in rating action reports is related to a higher level of conflict of interest faced by S&P. The information content of the tone in the reports will be more* (*less*) *valuable when the conflict of interest is low* (*high*).

We will employ four empirical proxies of conflict of interest identified in the literature to verify the first part of Hypothesis 2. To verify the second part of Hypothesis 2, we will use both the future rating changes and stock market returns to verify the information value of the tone from both S&P's perspective and the investors' perspective.

3. Data and Key Variables

In this section, we describe the key variables used and present their summary statistics.

3.1. The Construction of Linguistic Tone

Our key independent variable is linguistic tone. To quantify the positive and negative tone in each credit rating report, we use an automated Matlab program to count the number of positive and negative words by employing the word list defined by Loughran and McDonald (2011).[7] Following the prior literature, for each credit rating report, we define the positive (*TONE_POS*) and negative (*TONE_NEG*) tones by dividing the number of positive and negative words, respectively, by the total number of words in a report (Tetlock 2007, Tetlock et al. 2008). Our primary tone measure is the net tone (*NET_TONE*), measured as *TONE_NEG* minus *TONE_POS*, which indicates the overall negative tone in a rating report. We also list the top 10 positive and negative words used in the reports in Appendix A. To reduce the concern for measurement error, we also construct alternative tone measures by adopting a naïve Bayesian approach. The details of the approach are described in Appendix B.

3.2. The Definitions of Other Variables

To investigate the information content of the linguistic tone, we rely on *CAR* after subtracting the CRSP equally weighted buy-and-hold index return during the three-day event window surrounding a rating action as shown in Hand et al. (1992). We also construct two dummy variables that capture the future rating change to verify the information content of the tone: *DOWNGRADE_YR1* (*DOWNGRADE_YR2*) is a dummy variable that takes the value 1 if there is a downgrade within one year (two years) after the current rating action. In the robustness tests, we also construct four postevent excess returns: $CAR(2, 30)$, $CAR(2, 90)$, $CAR(2, 180)$, and $CAR(2, 360)$. The numerical numbers represent four time horizons of the returns of 30, 90, 180, and 360 days after the announcement.

The control variables used in this study include the contemporaneous rating actions, firm characteristics, and market conditions (e.g., Goh and Ederington 1993, Brennan et al. 1998, Avramov et al. 2009). For specific definitions of the control variables, please refer to Appendix C.

3.3. The Incentive Variables of S&P

To test Hypothesis 2, we construct four proxies to capture the conflict of interest faced by S&P. The first proxy is the length of the business relationship between S&P and the rated firm measured in natural logarithm of the calendar days between the current rating announcement day and the day of the first rating action. We name it *SP_HISTORY*. Using this measure, Mählmann (2011) finds that firms with longer relationships with CRAs tend to receive more favorable credit ratings. Thus, we use this measure to proxy for the level of conflict of interest faced by S&P.

Our second and third measures of conflict of interest come from the fee concern (Bar-Isaac and Shapiro 2013). CRAs charge a minimum rating fee for each bond issuance, and their fee schedules are primarily based on the dollar amount of the bond issuance.[8] Hence, S&P may face greater conflict of interest if it has to rate more products from the firm. The two variables are named *BOND_SIZE* and N_{BONDS}, where *BOND_SIZE* is the natural logarithm of the total outstanding amount of all rated bonds by S&P in a firm, and N_{BONDS} is the natural logarithm of the number of rated bonds by S&P in a firm.

Our last measure of conflict of interest is related to heightened attention from investors and regulators. In the recent financial crisis, CRAs were blamed for contributing to the crisis through their inflated

[7] Following Loughran and McDonald (2011), we remove the header, footer, and disclaimer in each report because these items are less meaningful in the measurement of tone. We have also revised the original word list by removing words relating to rating actions in credit rating action reports (e.g., downgrade and default) to make sure that the word list fits the context of credit rating action reports.

[8] For corporate bonds, CRAs charge fees in the range of three to five basis points of the par value of the issue (White 2002, Partnoy 2006).

credit ratings for structured financial products.[9] Since then, investors and regulators have closely scrutinized CRAs' rating models and business environments.[10] The closer monitoring by investors and regulators can increase the litigation risk faced by CRAs, which may reduce their incentive to cater investors or to inflate credit ratings. In a newswire search through Factiva from 1998 to 2008 of top circulated newspapers such as the *Financial Times*, *New York Times*, *Wall Street Journal*, *Washington Post*, and *USA Today*, we found only 10 articles that criticized major CRAs before 2006. We found a total of 38 articles that criticized CRAs in 2007 alone, and 51 articles in 2008. Hence, we construct a dummy variable, D_{2007}, that equals 1 after 2007 and 0 otherwise to represent a lower conflict of interest due to the litigation risk after 2007.

3.4. Sample Selection

Here we describe our sample selection procedure. First, we downloaded 5,080 rating reports based on the rating actions recorded in the S&P RatingsDirect database from 1998 to 2010. We removed 390 reports that did not have initial rating information. Next we removed 1,235 reports that did not have stock returns from CRSP. The data requirements of Standard Industry Classification (SIC) codes, surprise of unexpected earnings (SUE), and firm size led to a loss of another 409 reports. Our final sample consists of 3,046 credit rating action reports with 639 reports for credit watch events only and 1,270 reports for outlook events only. Table 1, Panel A, describes the sampling procedure.

3.5. Descriptive Statistics

Table 1, Panel B, presents the summary statistics of the key variables we employ. We find that there are more negative rating actions in our sample, as we have more rating downgrades than upgrades (22.42% versus 14.90%), more negative than positive credit watch events (18.75% versus 5.12%), and more negative than positive rating outlook actions (24.66% versus 12.18%). On average, the cumulative abnormal return $CAR(-1, 1)$ is at -1.08%, consistent with the fact that the majority of the reports consists of negative rather than positive rating actions. The average net tone (*NET_TONE*) is 0.00%, whereas the positive tone (*TONE_POS*) and negative tone (*TONE_NEG*) are 1.58% and 1.59%, respectively. Among the incentive variables, the average *SP_HISTORY* is 8.17, which represents 3,533 calendar days (about 9.8 years). Measures *BOND_SIZE* and N_{BONDS} have 1,058 missing observations due to the availability of individual corporate bond information in the Mergent Fixed Income Database (FISD). About half of the rating reports were released after January 2007 (48.75%).

4. Empirical Findings

We present the empirical results of the two main hypotheses in this section.

4.1. Information Value of Tone

To test Hypothesis 1 with respect to the informational value of tone, we regress $CAR(-1, 1)$ on our tone measures derived from the rating reports. Table 2 reports the regression results. Besides including two-way fixed effects of year and industry, we have clustered the standard errors by rating analysts and year and report the robust standard errors in this study.[11]

Model 1 in Table 2 presents the baseline relation between rating actions and stock returns. Stock returns are significantly and positively (negatively) related to rating upgrades (downgrades) at the 1% significance level. The market reaction to rating downgrades is greater in economic magnitude (-2.29%) than that to upgrades (0.31%), consistent with the prior literature (e.g., Holthausen and Leftwich 1986). Moreover, the stock returns are also significantly and negatively related to negative credit watch (-5.92%) and negative outlook (-3.99%) at the 10% significance level. These results indicate that credit watch and rating outlook provide incremental information beyond credit rating changes.

We find supporting evidence for Hypothesis 1 in Table 2 after we include *NET_TONE*. Specifically, Model 2 in Table 2 shows that *NET_TONE* is significantly negatively related to the returns at the 1% significance level, even after we add in various control variables. The economic magnitude of the market reaction to tone is -1.51% for a one-standard-deviation increase in the net tone. This significant relation remains robust as we add credit rating changes

[9] Since this crisis, investors and regulators have scrutinized CRAs' rating models and business environments, which increased the CRAs' exposure to litigation risk. The 2011 "Financial Crisis Inquiry Report" conducted by the Financial Crisis Inquiry Commission (2011, p. 25) states that "The three CRAs were key enablers of the financial meltdown. The mortgage-related securities at the heart of the crisis could not have been marketed and sold without their seal of approval.... Participants in the securitization industry realized that they needed to secure favorable credit ratings in order to sell structured products to investors. Investment banks therefore paid handsome fees to the CRAs to obtain the desired ratings."

[10] CRAs have received significantly more negative media coverage since 2007. Regulators have also applied several regulatory reforms to the credit rating industry. For example, the Dodd–Frank Act removes the regulatory references to credit ratings and exemption of CRAs from Regulation FD.

[11] The industry fixed effects are based on Fama and French 12-industry classification (i.e., SIC two-digit codes) available from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research. Clustering by analyst allows us to account for individual analysts' styles; year clusters allow consideration of the potential concern for market sentiment.

Table 1 Data Descriptions

Panel A: Sample selection

Source/adjustment	Sample size	Observations removed
Observations under investigation	10,397	
Adjusting for report availability	5,080	−5,317
Adjusting for initial rating availability	4,690	−390
Adjusting for stock return availability	3,455	−1,235
Adjusting for SIC availability	3,375	−80
Adjusting for SUE availability	3,358	−17
Adjusting for size availability	3,046	−312
Final sample size	3,046	

Panel B: Summary statistics

	N	Mean	Median	Std. dev.	Minimum	Maximum	Skewness	Kurtosis
CAR(−1, 1)	3,046	−0.0108	−0.0041	0.0993	−0.8717	0.9125	−1.0081	17.9823
UP	3,046	0.1490	0.0000	0.3562	0.0000	1.0000	1.9709	4.8844
DOWN	3,046	0.2242	0.0000	0.4171	0.0000	1.0000	1.3224	2.7488
NET_TONE	3,046	0.0000	−0.0002	0.0162	−0.0591	0.0653	0.0657	3.1483
NEG	3,046	0.0158	0.0142	0.0101	0.0000	0.0733	0.8386	3.9017
POS	3,046	0.0159	0.0148	0.0092	0.0000	0.0597	0.7899	3.9809
NEGWATCH	3,046	0.1875	0.0000	0.3903	0.0000	1.0000	1.6016	3.5652
POSWATCH	3,046	0.0512	0.0000	0.2205	0.0000	1.0000	4.0718	17.5796
NEGOL	3,046	0.2466	0.0000	0.4311	0.0000	1.0000	1.1761	2.3832
POSOL	3,046	0.1218	0.0000	0.3271	0.0000	1.0000	2.3128	6.3489
STABLEOL	3,046	0.3598	0.0000	0.4800	0.0000	1.0000	0.5842	1.3412
FALLEN_ANGEL	3,046	0.0230	0.0000	0.1499	0.0000	1.0000	6.3669	41.5378
RISING_STAR	3,046	0.0151	0.0000	0.1220	0.0000	1.0000	7.9519	64.2327
RATING_CHANGE	3,046	0.1090	0.0000	0.9122	−11.0000	5.0000	−0.7644	18.7779
INITIAL_RATING	3,046	11.5181	12.0000	3.3149	0.0000	22.0000	−0.3872	3.5207
LAST_CHANGE	3,046	2.7866	2.8621	0.5013	0.0000	3.7034	−1.0236	4.7519
SUE	3,046	−0.0774	0.0000	1.2961	−4.2249	7.2599	−0.0424	3.6802
SIZE	3,046	21.3235	21.3269	1.7079	14.9759	26.2641	−0.1429	3.1650
MKTRET	3,046	−0.0012	0.0103	0.0504	−0.1670	0.0985	−0.8300	4.0408
ΔVIX	3,046	0.0286	−0.0163	0.2069	−0.3196	0.9075	1.6184	6.8699
SP_HISTORY	3,046	8.1730	8.2141	0.9633	2.9957	10.2706	−0.5223	3.3119
BOND_SIZE	1,988	15.7937	15.5203	1.5087	11.8130	20.5076	0.3855	2.8311
N_{BONDS}	1,988	3.3461	3.1781	1.2779	0.0000	7.2717	0.3301	2.8863
D_{2007}	3,046	0.4875	0.0000	0.4999	0.0000	1.0000	0.0499	1.0025

Notes. This table describes, in Panel A, how we selected the final sample of 3,046 reports and, in Panel B, presents the summary statistics of the key dependent and independent variables used in this analysis. The detailed definitions of these variables are found in Appendix C.

(upgrades and downgrades), credit watch (positive watch and negative watch), and outlooks (positive, negative, and stable outlook) in Models 3–5, respectively. In Model 4, a one-standard-deviation increase in *NET_TONE* is related to a three-day excess return of −1.10%. These results reveal the unique information value contained in the tone of the rating reports.

Motivated by the evidence in prior literature that the market reacts more strongly to bad credit news than to good news (e.g., Beaver et al. 2006, Jorion and Zhang 2007), we replace *NET_TONE* by negative (*TONE_NEG*) and positive (*TONE_POS*) tone in Model 5. We find similar evidence in the market reaction toward tone. It is shown in Model 5 that the market reaction to *TONE_NEG* is more significant than that to *TONE_POS* at −1.06% (versus 0.17%).

Models 6 and 7 in Table 2 continue to show that the information value of the tone is robust even in the subsample of credit watch actions. These results are important because, different from a formal rating process required by regulators for credit rating changes (Credit Rating Agency Reform Act of 2006), there is no explicit rule in regulating other rating actions provided by CRAs. We find that the coefficient on *NET_TONE* on the credit watch sample is −1.3022 and significant at 1% level (Model 6). The coefficient on *TONE_NEG* is −1.9081 and statistically significant, whereas that on *TONE_POS* is not (Model 7), suggesting that the information content of tone is mainly driven by negative tone. For rating outlook, we find that the coefficient on *NET_TONE* is negative but insignificant at the 10% level. Overall, these results confirm that tone in rating action reports contains valuable information beyond rating changes and credit watch.

We also confirm that the tone indeed captures default-related information by using the future rating changes to proxy for the expected default risk.

Table 2 The Information Value of Tone During Credit Rating Actions

Dependent variable	*CAR*(−1, 1)								
Sample	All					Watchlist only		Outlook only	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
NET_TONE		−0.9318***	−0.6914***	−0.6771*		−1.3022**		−0.4001	
		(−4.46)	(−2.76)	(−1.89)		(−2.26)		(−1.60)	
TONE_NEG					−1.0450*		−1.9081***		−0.3231
					(−1.66)		(−2.67)		(−0.83)
TONE_POS					0.1868		0.1885		0.4784
					(0.86)		(0.15)		(1.64)
UP	0.0031***	−0.0011	−0.0014	−0.0037	−0.0043				
	(3.79)	(−0.15)	(−0.18)	(−0.61)	(−0.71)				
DOWN	−0.0229***	−0.0080	−0.0116	−0.0096	−0.0097				
	(−4.06)	(−1.09)	(−1.22)	(−1.09)	(−1.10)				
POSWATCH	−0.0114		0.0059	−0.0288	−0.0251	−0.0684***	−0.0560*		
	(−0.62)		(0.74)	(−1.63)	(−1.38)	(−2.70)	(−1.81)		
NEGWATCH	−0.0592**		−0.0181	−0.0540*	−0.0517	−0.0809*	−0.0758		
	(−2.14)		(−1.36)	(−1.65)	(−1.52)	(−1.76)	(−1.55)		
POSOL	−0.0220			−0.0373**	−0.0319			−0.0069	−0.0071
	(−1.16)			(−2.11)	(−1.58)			(−0.34)	(−0.35)
NEGOL	−0.0399*			−0.0391	−0.0349			−0.0103	−0.0106
	(−1.83)			(−1.54)	(−1.26)			(−0.43)	(−0.44)
STABLEOL	−0.0253			−0.0360*	−0.0315			−0.0102	−0.0104
	(−1.39)			(−1.86)	(−1.47)			(−0.46)	(−0.47)
FALLEN_ANGEL		−0.0238*	−0.0232*	−0.0212*	−0.0209*				
		(−1.91)	(−1.89)	(−1.74)	(−1.70)				
RISING_STAR		−0.0066	−0.0068	−0.0065	−0.0073				
		(−0.82)	(−0.85)	(−0.82)	(−0.94)				
RATING_CHANGE		−0.0019	−0.0014	−0.0038	−0.0039				
		(−0.42)	(−0.30)	(−0.94)	(−0.98)				
INITIAL_RATING		0.0001	−0.0002	−0.0005	−0.0006	−0.0051	−0.0052	0.0004	0.0004
		(0.05)	(−0.15)	(−0.38)	(−0.39)	(−0.96)	(−0.98)	(0.51)	(0.50)
LAST_CHANGE		−0.0040	−0.0038	−0.0023	−0.0023	−0.0146	−0.0140	−0.0100**	−0.0100**
		(−0.62)	(−0.59)	(−0.36)	(−0.36)	(−1.07)	(−1.07)	(−2.45)	(−2.46)
SUE		0.0020	0.0019	0.0019	0.0018	0.0069	0.0066	0.0021	0.0021
		(0.90)	(0.86)	(0.90)	(0.81)	(1.36)	(1.24)	(0.78)	(0.80)
SIZE		0.0021	0.0022	0.0021	0.0021	−0.0079	−0.0081	0.0011	0.0011
		(1.36)	(1.42)	(1.44)	(1.42)	(−0.96)	(−0.97)	(0.58)	(0.57)
MKTRET		0.1025***	0.1045***	0.0995***	0.0935***	0.0837	0.0745	0.0493	0.0504
		(3.30)	(3.38)	(3.70)	(3.32)	(0.39)	(0.37)	(1.04)	(1.03)
Δ*VIX*		0.0053	0.0066	0.0067	0.0065	0.0051	0.0039	0.0160**	0.0160**
		(0.64)	(0.75)	(0.80)	(0.76)	(0.14)	(0.11)	(2.18)	(2.17)
INTERCEPT	0.0863***	0.0159	0.0241	0.0552	0.0623	0.6252**	0.6386***	0.0093	0.0079
	(4.78)	(0.33)	(0.48)	(0.88)	(1.05)	(2.52)	(2.62)	(0.26)	(0.22)
N	3,046	3,046	3,046	3,046	3,046	639	639	1,270	1,270
R^2	0.05	0.05	0.06	0.06	0.06	0.14	0.14	0.03	0.03
Economic significance (%)		−1.51	−1.12	−1.10	−1.06	−2.11	−1.93	−0.65	−0.33

Notes. This table presents the information value of tone during credit rating actions announced by S&P from 1998 to 2010. The dependent variable is *CAR*(−1, 1). *TONE_POS* is the positive tone, and *TONE_NEG* is the negative tone; *NET_TONE* is *TONE_NEG* minus *TONE_POS*. All other variables are defined in Appendix C. The *t*-values are calculated based on robust standard errors clustered by both analyst and year. We include year and industry fixed effects. The economic significance is reported for *NET_TONE* in Models 2–4, 6, and 8, and for *TONE_NEG* in Models 5, 7, and 9.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Specifically, we employ one-year-ahead and two-year-ahead credit rating downgrades (*DOWNGRADE_YR1* and *DOWNGRADE_YR2*) as the dependent variables and regress them on tone. Table 3 presents the results.

Model 1 of Table 3 reports the result for the whole sample and shows that the coefficient on *NET_TONE* is 2.9809 and is significant at the 1% level. In Models 2 and 3, where we report results on credit watch and rating outlook subsamples, respectively, the coefficients on *NET_TONE* remain positive and significant at the 1% level. In Models 4–6, we separate *NET_TONE* into *TONE_NEG* and *TONE_POS* and find that *TONE_NEG* is the main driver for the future rating changes at the 1% significance level, instead of *TONE_POS*. We further extend our analysis to the two-year future rating change in Model 7 to Model 9 and find that the *NET_TONE* is significantly and positively related to future downgrades. In terms of the economic significance, a one-standard-deviation increase in *NET_TONE* can increase the downgrade probability up to 5.49% in one year, shown in Model 2, and 4.65% in two years, shown in Model 9. Taken together, the results confirm that tone contains default-related information, which supports Hypothesis 1.

Last, we eliminate the concern that the market reaction to tone is irrational and the market may subsequently correct itself. We do so by examining the postannouncement drift of the release of the credit rating action reports. Specifically, we regress long-run excess stock returns subsequent to the rating action announcements on tone. Table 4 reports the results.

The results in Table 4 show that *NET_TONE*, *TONE_NEG*, and *TONE_POS* are insignificantly related to postannouncement stock returns from day 2 onward (till 360 days) at the 10% significance level in seven out of eight model specifications. These results indicate that there is no systematic pattern in return corrections after the rating action announcements.

Overall, we find compelling and robust empirical support for Hypothesis 1 that tone contains valuable default-related information for the stock market beyond credit rating actions.

4.2. The Incentives of S&P

In this section, we explore the role of conflict of interest in the provision of tone in rating reports. We employ four incentive measures to proxy for S&P's conflict of interest: *SP_RELATION*, *BOND_SIZE*, N_{BONDS}, and D_{2007}, where *SP_RELATION* measures the length of S&P's rating history with the rated firm; *BOND_SIZE* and N_{BONDS} measure the dollar amount and number of rated bonds by S&P, respectively; and D_{2007} measures the heightened litigation risk by investors and regulators after 2007. To understand how these proxies drive the tone, we employ *NET_TONE*, *TONE_NEG*, and *TONE_POS* as the key dependent variables. Given the extant literature, we expect the *NET_TONE* to be negatively associated with *SP_RELATION*, *BOND_SIZE*, and N_{BONDS}, and to be positively related to D_{2007}. When we include D_{2007}, we drop the year fixed effects from the model specification. Table 5 presents the results.[12]

To our surprise, we find that *SP_RELATION*, *BOND_SIZE*, and N_{BONDS} are all positively associated with *NET_TONE*, shown in Models 1–3 of Table 5. These results indicate that the high conflict of interest is not associated with more favorable net tone, but instead is significantly related to more negative net tone.[13] To remove the concern that the *NET_TONE* captures both positive and negative tone at the same time, we rerun the regression by replacing the dependent variable by *TONE_NEG* and *TONE_POS* from Model 5 to Model 12, respectively. We find that these three proxies of conflict of interest are significantly related to *TONE_NEG* at the 1% significance level, shown in Models 5–7. They are insignificantly related to *TONE_POS* at the 10% level, shown in Models 9–11. These results suggest that the conflict of interest is not related to the inflation of tone, rejecting Hypothesis 2. This is a novel finding and is different from the existing literature where rating inflation is founded to be significantly related to the conflict of interest.

Whereas the other three incentives capture the high level of conflict of interest, the dummy variable D_{2007} captures a low level of conflict of interest due to litigation risk. Model 4 in Table 5 shows a positive relation between litigation risk and net tone, suggesting that the lower conflict of interest is related to more negative net tone. When we split the net tone into the positive and negative tone, shown in Models 8 and 12 of Table 5, we find that the litigation risk leads to less positive tone (*TONE_POS*) at the 1% significance level, whereas the litigation risk is insignificantly related to *TONE_NEG* at the 10% significance level. These results indicate that the litigation risk can serve as an effective disciplinary channel for CRAs to reduce the conflict of interest, as they tend to use less positive words in the rating reports.

Given the above findings that seem to contradict Hypothesis 2, we further explore whether the information content of tone varies with respect to the level of conflict of interest. We use two proxies for the information content of tone, the future rating change (from S&P's perspective) and the stock returns (from the investors' perspective), as before in testing Hypothesis 1. The results are presented in Table 6.

Table 6 shows the predictability of *NET_TONE* for future rating changes in the one-year horizon by interacting *NET_TONE* with the four incentive variables. We define *INCENTIVE* as 1 if *SP_RELATION* is greater than the median, *BOND_SIZE* is greater

[12] We include a dummy variable D_{MISSING} that equals 1 if the incentive measures such as N_{BONDS} and *BOND_SIZE* are missing from our sample. The loss of observations is due to the merge with the Mergent FISD data. In the analysis, we replace the missing incentive variables by zero and include D_{MISSING} to control for the effect of the missing observations. Moreover, for Models 4, 8, and 12, we include only the industry fixed effects since we have included D_{2007}.

[13] It is possible that the credit ratings tend to drift down over time because firms may go bankrupt or exit from being rated. Hence, *SP_RELATION* may plausibly be related to declining credit quality of the firm over the time.

Table 3 The Information Value of Tone in Predicting Future Rating Changes

Dependent variable	*DOWNGRADE_YR1*						*DOWNGRADE_YR2*		
Sample	All	Watchlist	Outlook	All	Watchlist	Outlook	All	Watchlist	Outlook
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
NET_TONE	2.9809***	3.3874***	2.8529***				2.3498***	1.1973	2.8673***
	(4.88)	(4.64)	(3.24)				(3.30)	(0.83)	(3.42)
TONE_NEG				4.7012***	5.4943***	5.5653***			
				(5.69)	(3.27)	(4.29)			
TONE_POS				−0.6884	0.4851	−0.0925			
				(−0.81)	(0.27)	(−0.07)			
UP	−0.0830***			−0.0800***			−0.0818**		
	(−3.84)			(−3.54)			(−2.45)		
DOWN	−0.0177			−0.0172			−0.0271		
	(−0.64)			(−0.63)			(−1.02)		
POSWATCH	−0.1017**	−0.0717		−0.1190***	−0.1152		−0.0667	−0.0372	
	(−2.22)	(−0.72)		(−2.74)	(−1.31)		(−1.30)	(−0.55)	
NEGWATCH	0.2861***	0.2304**		0.2751***	0.2127**		0.2801***	0.3064***	
	(5.90)	(2.50)		(5.82)	(2.37)		(4.70)	(5.19)	
POSOL	−0.1299**		−0.1162**	−0.1550***		−0.1260**	−0.1250**		−0.1355
	(−2.57)		(−2.44)	(−3.24)		(−2.33)	(−2.43)		(−1.39)
NEGOL	0.0633		0.1116*	0.0436		0.1015	0.1273**		0.1353
	(1.32)		(1.78)	(0.91)		(1.46)	(2.09)		(1.36)
STABLEOL	−0.0874*		−0.0713	−0.1088**		−0.0798	−0.0492		−0.0600
	(−1.76)		(−1.10)	(−2.25)		(−1.13)	(−0.94)		(−0.58)
FALLEN_ANGEL	0.1160***			0.1147***			0.0796*		
	(2.78)			(2.79)			(1.77)		
RISING_STAR	0.0117			0.0155			−0.0013		
	(0.29)			(0.40)			(−0.02)		
RATING_CHANGE	−0.0388***			−0.0382***			−0.0348***		
	(−6.24)			(−5.77)			(−5.02)		
INITIAL_RATING	−0.0134***	−0.0408***	−0.0016	−0.0133***	−0.0404***	−0.0018	−0.0183***	−0.0378**	−0.0079**
	(−3.96)	(−3.95)	(−0.47)	(−4.16)	(−4.10)	(−0.54)	(−3.51)	(−2.32)	(−2.34)
LAST_CHANGE	0.0157	−0.0001	0.0435*	0.0157	−0.0023	0.0432*	0.0190	−0.0007	0.0439*
	(1.11)	(−0.00)	(1.82)	(1.11)	(−0.04)	(1.81)	(0.84)	(−0.02)	(1.74)
SUE	−0.0290***	−0.0391***	−0.0179***	−0.0284***	−0.0380***	−0.0168***	−0.0274***	−0.0329***	−0.0173
	(−4.97)	(−4.18)	(−3.21)	(−4.88)	(−4.25)	(−3.12)	(−3.34)	(−5.66)	(−1.56)
SIZE	−0.0160***	−0.0476**	−0.0018	−0.0160***	−0.0469**	−0.0026	−0.0157*	−0.0245	−0.0137
	(−2.98)	(−2.01)	(−0.25)	(−3.07)	(−2.02)	(−0.36)	(−1.70)	(−0.94)	(−1.46)
MKTRET	0.1641	−0.9517***	0.1471	0.1922	−0.9199***	0.1873	0.3072	−0.9674***	0.1894
	(0.55)	(−2.87)	(0.40)	(0.64)	(−2.64)	(0.53)	(1.22)	(−4.19)	(0.51)
Δ*VIX*	0.0193	−0.0878	0.0402	0.0201	−0.0836	0.0402	0.0448*	−0.2002***	0.1112
	(0.56)	(−1.32)	(0.58)	(0.56)	(−1.24)	(0.57)	(1.92)	(−3.02)	(1.53)
INTERCEPT	0.6965***	1.5414**	0.2538	0.6633***	1.4949***	0.2020	0.8779***	1.0107	0.5898***
	(5.26)	(2.56)	(0.84)	(5.51)	(2.63)	(0.70)	(3.73)	(1.43)	(2.62)
N	3,046	639	1,270	3,046	639	1,270	3,046	639	1,270
R^2	0.29	0.37	0.18	0.29	0.38	0.19	0.22	0.30	0.16
Economic significance (%)	4.83	5.49	4.62	4.75	5.55	5.62	3.81	1.94	4.65

Notes. This table presents the information value of tone in predicting future rating changes by S&P from 1998 to 2010. The dependent variables are two dummy variables that take the value 1 if there are rating downgrades within one or two years after the current rating action, respectively, and 0 otherwise. *TONE_POS* is positive tone, and *TONE_NEG* is negative tone; *NET_TONE* is *TONE_NEG* minus *TONE_POS*. All other variables are defined in Appendix C. The *t*-values are calculated based on robust standard errors clustered by both analyst and year. We include year and industry fixed effects. The economic significance is reported for *NET_TONE* in Models 1–3 and Models 7–9, and for *TONE_NEG* in Models 4–6.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

than the median (in the nonmissing sample), N_{BONDS} is greater than the median (in the nonmissing sample), and D_{2007} takes the value 1, and 0 otherwise. Our results show that the *NET_TONE* is positively and significantly related to future downgrade at the 1% significance level when the conflict of interest is low, as the *INCENTIVE* variable equals 0 in Models 1–3 and equals 1 in Model 4 (because of litigation risk). More interestingly, the direct statistical tests show that *NET_TONE* is also significantly related to the future downgrade when the conflict of interest is high at the 1% significance level (which is the statistical significance of the sum of the coefficients on [1] *INCENTIVE* and [2] *NET_TONE* × *INCENTIVE*).

Table 4 The Information Value of Tone in Predicting Future Stock Returns

Dependent variables	*CAR* (2, 30)	*CAR* (2, 90)	*CAR* (2, 180)	*CAR* (2, 360)	*CAR* (2, 30)	*CAR* (2, 90)	*CAR* (2, 180)	*CAR* (2, 360)
NET_TONE	0.0072	−0.0833	0.2428	−0.7172				
	(0.04)	(−0.14)	(0.30)	(−1.10)				
TONE_NEG					−0.1466	−0.4704	−0.0297	−1.5911***
					(−0.60)	(−0.73)	(−0.05)	(−3.81)
TONE_POS					−0.2122	−0.4326	−0.6060	−0.4474
					(−0.39)	(−0.45)	(−0.48)	(−0.36)
UP	0.0463***	0.0823***	0.0861***	0.0838***	0.0460***	0.0816***	0.0856***	0.0823***
	(5.05)	(4.32)	(3.01)	(3.18)	(4.94)	(4.26)	(3.01)	(3.09)
DOWN	0.0044	0.0093	0.0410	0.0686**	0.0043	0.0092	0.0409	0.0683**
	(0.42)	(0.51)	(1.15)	(2.31)	(0.42)	(0.50)	(1.15)	(2.33)
POSWATCH	−0.0178	−0.0332	−0.0208	−0.0479	−0.0162	−0.0293	−0.0180	−0.0391
	(−0.57)	(−0.79)	(−0.35)	(−0.97)	(−0.50)	(−0.69)	(−0.30)	(−0.77)
NEGWATCH	−0.0152	−0.0297	−0.0438	−0.0372	−0.0142	−0.0272	−0.0421	−0.0316
	(−0.58)	(−0.74)	(−0.92)	(−0.91)	(−0.53)	(−0.67)	(−0.88)	(−0.78)
POSOL	−0.0259	−0.0454	−0.0476	−0.0659	−0.0237	−0.0398	−0.0437	−0.0532
	(−1.02)	(−1.04)	(−0.93)	(−1.42)	(−0.88)	(−0.92)	(−0.85)	(−1.15)
NEGOL	−0.0187	−0.0455	−0.0509	−0.0654**	−0.0170	−0.0411	−0.0477	−0.0554**
	(−0.73)	(−1.14)	(−1.15)	(−2.21)	(−0.63)	(−1.04)	(−1.11)	(−2.01)
STABLEOL	−0.0308	−0.0628	−0.0720	−0.1035**	−0.0289	−0.0579	−0.0686	−0.0927**
	(−1.19)	(−1.52)	(−1.52)	(−2.38)	(−1.07)	(−1.41)	(−1.46)	(−2.16)
FALLEN_ANGEL	−0.0068	−0.0195	−0.0636*	−0.0523*	−0.0067	−0.0192	−0.0634*	−0.0516*
	(−0.63)	(−0.83)	(−1.89)	(−1.95)	(−0.63)	(−0.82)	(−1.87)	(−1.89)
RISING_STAR	−0.0069	−0.0491**	−0.0357	−0.0186	−0.0072	−0.0499**	−0.0363	−0.0206
	(−0.67)	(−2.37)	(−1.55)	(−0.58)	(−0.71)	(−2.48)	(−1.59)	(−0.68)
RATING_CHANGE	0.0170**	0.0261**	0.0285*	0.0106	0.0169**	0.0260**	0.0284*	0.0103
	(2.31)	(2.17)	(1.74)	(0.82)	(2.26)	(2.13)	(1.72)	(0.78)
INITIAL_RATING	0.0000	−0.0022	−0.0031	−0.0066***	−0.0000	−0.0022	−0.0031	−0.0067***
	(0.01)	(−0.92)	(−1.16)	(−2.78)	(−0.00)	(−0.93)	(−1.16)	(−2.79)
LAST_CHANGE	−0.0322***	−0.0462***	−0.0544***	−0.0733***	−0.0322***	−0.0462***	−0.0544***	−0.0733***
	(−3.66)	(−4.67)	(−3.93)	(−4.43)	(−3.67)	(−4.70)	(−3.95)	(−4.48)
SUE	0.0129***	0.0261***	0.0351***	0.0355***	0.0128***	0.0260***	0.0350***	0.0352***
	(5.16)	(3.24)	(3.94)	(3.59)	(5.25)	(3.22)	(3.93)	(3.60)
SIZE	−0.0007	−0.0087	−0.0112	−0.0201**	−0.0007	−0.0087	−0.0112	−0.0201**
	(−0.30)	(−1.64)	(−1.65)	(−2.09)	(−0.30)	(−1.62)	(−1.64)	(−2.06)
MKTRET	−0.0277	−0.1597	0.1403	−0.2158	−0.0302	−0.1660	0.1359	−0.2300
	(−0.38)	(−0.72)	(0.33)	(−1.17)	(−0.41)	(−0.73)	(0.32)	(−1.23)
Δ*VIX*	0.0511*	−0.0131	−0.0177	−0.0827*	0.0510*	−0.0132	−0.0178	−0.0831*
	(1.87)	(−0.39)	(−0.25)	(−1.69)	(1.87)	(−0.39)	(−0.25)	(−1.68)
INTERCEPT	0.1433***	0.3081***	0.4050**	0.8010***	0.1463***	0.3156***	0.4103**	0.8179***
	(2.60)	(2.66)	(2.35)	(3.69)	(2.70)	(2.84)	(2.41)	(3.80)
N	3,046	3,046	3,046	3,046	3,046	3,046	3,046	3,046
R^2	0.03	0.04	0.06	0.05	0.03	0.04	0.06	0.05

Notes. This table presents the information value of tone in predicting future stock returns from 1998 to 2010. The dependent variables are *CAR*(2, 30), *CAR*(2, 90), *CAR*(2, 180), and *CAR*(2, 360). *TONE_POS* is the positive tone, and *TONE_NEG* is the negative tone; *NET_TONE* is *TONE_NEG* minus *TONE_POS*. All other variables are defined in Appendix C. The t-values are calculated based on robust standard errors clustered by both rating analyst and year. We include year and industry fixed effects.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

These results indicate that tone contains additional default-related information regardless of the level of the conflict of interest from the perspective of S&P, rejecting Hypothesis 2. These results are consistent with our previous findings that tone is not inflated by conflict of interest faced by S&P.

Models 5–8 in Table 6 reports the information content of tone in the stock returns by conditioning on the level of conflict of interest.[14] This test is important because we are testing the value of tone from the investors' (or the stock market's) perspective. We find that the *NET_TONE* is significantly related to stock returns when the conflict of interest is low at the 10%

[14] Similar to Table 5, we include only industry fixed effects in Models 4, 8, and 12 since we have D_{2007}.

Table 5 The Incentives of S&P vs. Tone

Dependent variable	*NET_TONE*				*TONE_NEG*				*TONE_POS*			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
SP_RELATION	0.0007***				0.0009***				0.0002			
	(3.01)				(4.94)				(0.96)			
BOND_SIZE		0.0007***				0.0007***				0.0000		
		(3.03)				(5.01)				(0.11)		
N_{BONDS}			0.0008***				0.0008***				0.0001	
			(2.92)				(4.98)				(0.34)	
D_{2007}				0.0037***				0.0010				−0.0026***
				(3.04)				(0.92)				(−4.72)
$D_{MISSING}$		0.0106***	0.0021**			0.0108***	0.0022***			0.0001	0.0000	
		(2.99)	(2.41)			(4.70)	(3.37)			(0.06)	(0.10)	
UP	−0.0049***	−0.0049***	−0.0050***	−0.0050***	−0.0035***	−0.0035***	−0.0036***	−0.0036***	0.0014***	0.0014***	0.0014***	0.0014***
	(−5.36)	(−5.61)	(−5.71)	(−5.21)	(−4.01)	(−4.26)	(−4.35)	(−3.90)	(3.39)	(3.30)	(3.34)	(3.39)
DOWN	0.0058***	0.0058***	0.0058***	0.0061***	0.0031***	0.0031***	0.0031***	0.0034***	−0.0027***	−0.0027***	−0.0027***	−0.0027***
	(9.00)	(8.86)	(8.91)	(9.74)	(6.58)	(6.36)	(6.38)	(6.95)	(−17.39)	(−16.76)	(−17.72)	(−176.71)
POSWATCH	−0.0167***	−0.0166***	−0.0167***	−0.0168***	−0.0051***	−0.0051***	−0.0051***	−0.0053***	0.0116***	0.0116***	0.0116***	0.0115***
	(−9.80)	(−9.50)	(−9.70)	(−10.02)	(−3.75)	(−3.69)	(−3.82)	(−3.92)	(9.66)	(9.61)	(9.60)	(9.67)
NEGWATCH	0.0126***	0.0125***	0.0125***	0.0124***	0.0100***	0.0099***	0.0099***	0.0099***	−0.0026***	−0.0026***	−0.0026***	−0.0026***
	(19.97)	(18.36)	(18.91)	(19.61)	(20.75)	(17.38)	(17.81)	(16.25)	(−3.56)	(−3.62)	(−3.61)	(−3.78)
POSOL	−0.0132***	−0.0133***	−0.0133***	−0.0136***	−0.0011	−0.0012	−0.0012	−0.0016	0.0121***	0.0121***	0.0121***	0.0120***
	(−6.03)	(−5.88)	(−5.93)	(−6.51)	(−0.93)	(−0.97)	(−0.99)	(−1.35)	(8.77)	(8.71)	(8.78)	(9.04)
NEGOL	0.0060***	0.0059***	0.0059***	0.0060***	0.0084***	0.0083***	0.0083***	0.0084***	0.0024***	0.0024***	0.0024***	0.0024***
	(6.16)	(5.74)	(5.75)	(6.37)	(9.63)	(8.97)	(8.99)	(8.98)	(3.15)	(3.18)	(3.18)	(3.37)
STABLEOL	−0.0061***	−0.0061***	−0.0061***	−0.0062***	0.0020**	0.0019*	0.0019*	0.0018*	0.0081***	0.0080***	0.0080***	0.0080***
	(−4.44)	(−4.29)	(−4.33)	(−4.68)	(1.99)	(1.85)	(1.86)	(1.77)	(8.24)	(8.21)	(8.24)	(8.61)
FALLEN_ANGEL	−0.0003	−0.0004	−0.0004	−0.0006	0.0002	0.0001	0.0001	−0.0001	0.0005	0.0005	0.0005	0.0005
	(−0.25)	(−0.30)	(−0.31)	(−0.49)	(0.21)	(0.11)	(0.09)	(−0.08)	(0.70)	(0.69)	(0.69)	(0.82)
RISING_STAR	0.0003	0.0003	0.0003	−0.0002	−0.0008	−0.0007	−0.0008	−0.0013	−0.0010	−0.0011	−0.0011	−0.0011
	(0.21)	(0.26)	(0.23)	(−0.18)	(−0.87)	(−0.82)	(−0.89)	(−1.49)	(−0.88)	(−0.89)	(−0.88)	(−0.95)

Table 5 (Continued)

Dependent variable	*NET_TONE*				*TONE_NEG*				*TONE_POS*			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
RATING CHANGE	−0.0006**	−0.0007**	−0.0007**	−0.0007**	−0.0005	−0.0006*	−0.0006*	−0.0005	0.0002	0.0002	0.0002	0.0001
	(−1.99)	(−2.48)	(−2.53)	(−2.10)	(−1.28)	(−1.74)	(−1.75)	(−1.47)	(1.43)	(1.53)	(1.51)	(1.29)
INITIAL RATING	0.0003**	0.0002	0.0002	0.0003	0.0002	0.0001	0.0001	0.0001	−0.0001*	−0.0002**	−0.0002**	−0.0002**
	(2.04)	(1.60)	(1.61)	(1.63)	(1.30)	(0.64)	(0.65)	(0.60)	(−1.77)	(−2.03)	(−2.03)	(−2.35)
LAST CHANGE	−0.0016***	−0.0014***	−0.0014***	−0.0018***	−0.0010***	−0.0007**	−0.0007**	−0.0013***	0.0006***	0.0007***	0.0007***	0.0005***
	(−4.33)	(−3.45)	(−3.66)	(−4.43)	(−2.66)	(−2.12)	(−2.22)	(−3.44)	(4.96)	(4.64)	(4.85)	(3.30)
SUE	−0.0014***	−0.0014***	−0.0014***	−0.0014***	−0.0010***	−0.0009***	−0.0009***	−0.0010***	0.0005***	0.0005***	0.0005***	0.0005***
	(−9.13)	(−8.27)	(−8.29)	(−9.75)	(−11.50)	(−9.31)	(−9.52)	(−11.33)	(4.49)	(4.51)	(4.54)	(4.77)
SIZE	−0.0008***	−0.0010***	−0.0010***	−0.0008***	−0.0005***	−0.0007***	−0.0007***	−0.0006***	0.0003*	0.0003**	0.0003**	0.0002
	(−3.34)	(−4.13)	(−3.96)	(−3.04)	(−2.74)	(−4.20)	(−3.75)	(−2.66)	(1.95)	(2.12)	(2.07)	(1.58)
MKTRET	−0.0040	−0.0042	−0.0041	−0.0069	−0.0095*	−0.0096*	−0.0095*	−0.0126*	−0.0055**	−0.0054**	−0.0055**	−0.0057
	(−0.56)	(−0.58)	(−0.57)	(−0.78)	(−1.67)	(−1.65)	(−1.66)	(−1.78)	(−2.31)	(−2.30)	(−2.32)	(−1.48)
Δ*VIX*	0.0019**	0.0020**	0.0021**	0.0005	0.0008	0.0010	0.0010	−0.0007**	−0.0011**	−0.0011**	−0.0011**	−0.0012*
	(1.96)	(1.99)	(1.98)	(0.57)	(1.00)	(1.09)	(1.09)	(−2.12)	(−2.36)	(−2.33)	(−2.32)	(−1.69)
INTERCEPT	0.0047	0.0051	0.0119**	0.0185**	0.0086*	0.0099**	0.0169***	0.0252***	0.0039	0.0047	0.0050	0.0067
	(0.77)	(0.84)	(2.10)	(2.51)	(1.79)	(2.23)	(4.05)	(4.08)	(0.91)	(1.16)	(1.38)	(1.56)
N	3,046	3,046	3,046	3,046	3,046	3,046	3,046	3,046	3,046	3,046	3,046	3,046
R^2	0.58	0.58	0.58	0.57	0.43	0.43	0.43	0.41	0.49	0.49	0.49	0.48

Notes. This table presents the link between the net tone, positive tone, and negative tone and S&P's concern about rating fees and reputation capital. The sample data are from 1998 to 2010. The dependent variables are net tone (*NET_TONE*), positive tone (*TONE_POS*), and negative tone (*TONE_NEG*). *SP_RELATION* is the natural logarithm of the number of days between the announcement date and the day when S&P first rated the firm. *BOND_SIZE* is the natural logarithm of the total amount outstanding of all the bonds within each firm. N_{BONDS} is the natural logarithm of the number of S&P rated bonds within each firm. D_{2007} is a dummy variable that equals 1 if the release of rating report is in the post-2007 period and 0 otherwise. D_{FOLLOWER} is a dummy variable that equals 1 if S&P takes a rating action following other rating agency on the same firm within a 10-day window and 0 otherwise. D_{MISSING} is a dummy variable that equals 1 if there is no outstanding bond being rated by S&P recorded in the Mergent FISD and 0 otherwise. All other variables are defined in Appendix C. The *t*-values are calculated based on robust standard errors clustered by both rating analyst and year. We include year and industry fixed effects (except in Models 4, 8, and 12, in which we include only industry fixed effects).

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6 The Information Value of the Reports and the Incentives of S&P

Dependent variable	*DOWNGRADE_YR1*				*CAR*(−1, 1)			
Incentive variable	*SP_RELATION*	*BOND_SIZE*	N_{BONDS}	D_{2007}	*SP_RELATION*	*BOND_SIZE*	N_{BONDS}	D_{2007}
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
[1] *NET_TONE*	2.5135***	2.7160***	2.3173***	2.5699***	−0.7364**	−1.0106**	−0.9695*	−1.0625***
	(2.82)	(2.95)	(3.31)	(3.07)	(−2.24)	(−2.37)	(−1.90)	(−2.99)
[2] *NET_TONE* × *INCENTIVE*	0.6266	0.1069	0.9804	0.5602	0.1499	0.3314	0.2198	0.8975
	(0.57)	(0.10)	(0.65)	(0.76)	(0.81)	(0.69)	(0.52)	(1.52)
[3] *INCENTIVE*	−0.4966	0.0579	0.3043	−0.2478	0.0322	−0.1329	−0.0774	0.0435
	(−1.15)	(0.13)	(0.78)	(−1.58)	(0.29)	(−1.20)	(−0.92)	(0.43)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,046	1,988	1,988	3,046	3,046	1,988	1,988	3,046
R^2	0.29	0.30	0.30	0.27	0.07	0.10	0.10	0.07
Coefficient [1] + [2]	3.1400***	2.8229***	3.2977***	3.1300***	−0.5864	−0.6791	−0.7497*	−0.1650
p-value	0.000	0.001	0.006	0.001	0.121	0.190	0.077	0.722

Notes. This table presents the information value of tone when different incentives are present. The sample data span from 1998 to 2010. The dependent variables are the dummy variable that takes the value 1 if there is rating downgrade within one year after the current rating action and 0 otherwise in Models 1–4, and the cumulative abnormal return within the (−1, 1) event window for Models 5–8. *NET_TONE* is *TONE_NEG* minus *TONE_POS*. The incentive variable takes the value 1 if *SP_RELATION* is greater than the median, *BOND_SIZE* is greater than the median, N_{BONDS} is greater than the median, and D_{2007} equals 1, and 0 otherwise. *SP_RELATION* is the natural logarithm of the number of days between the announcement date and the day when S&P first rated the firm. *BOND_SIZE* is the natural logarithm of the total amount outstanding of all the bonds within each firm. N_{BONDS} is the natural logarithm of the number of S&P rated bonds within each firm. D_{2007} is a dummy variable that equals 1 if the release of rating report is in the post-2007 period and 0 otherwise. All other control variables are the same as in Table 5 and are defined in Appendix C. We have also included all the interaction terms of incentive and the control variables. The *t*-values are calculated based on robust standard errors clustered by year. We include year and industry fixed effects in Models 1–3 and Models 5–7. We include industry fixed effects in Models 4 and 8.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

significance level in Models 5–7. When the conflict of interest is high, we find that the market reaction is weaker (i.e., statistically significant in two out of four models at the 10% significance level in Models 7 and 8). Overall, these results show that investors still value the tone even when the conflict of interest is high, rejecting Hypothesis 2.

More interestingly, we find that the coefficient on *NET_TONE* is not significant in the post-2007 period at the 10% significance level, shown in Model 8 in Table 6 (for coefficient [1] + [2]). Linking the earlier result that *NET_TONE* is significantly related to future downgrade in Model 4, the current result indicates that the investors are losing confidence in the information provided by CRAs after 2007, even though CRAs carry out the real actions following their reports. This is consistent with heightened public criticism on the CRAs' rating inflation behavior for structured credit products.[15] It seems that the dampening of the CRAs' reputation also spilled over to the corporate rating sector. As shown in Figure 1, the cumulative returns of the S&P and Moody's significantly declined after 2007.

[15] We note that financial firms often issue large amount of structure finance products and may have greater bargaining power to influence information provided by CRAs. However, we have only 41 observations from this sector. Hence, we cannot meaningfully verify this plausible story in our sample.

Overall, our empirical evidence does not seem to support Hypothesis 2 that the conflict of interest may lead to more favorable net tone. We find that a higher level of conflict of interest is related to more negative net tone. We also find that the tone always contains new information beyond rating actions from CRAs' perspective, regardless of the level of conflict of interest. Our findings suggest that, unlike credit rating actions, credit rating action reports are less affected by the conflict of interest faced by CRAs. This is not surprising because the credit ratings had been explicitly used as references for credit quality in regulations and rules before 2009 (e.g., Brown et al. 2015). These results suggest that credit rating action reports maybe a valuable placeholder for CRAs to accumulate their reputation capital, which is claimed to be the core of CRAs' survival (e.g., Partnoy 1999, Covitz and Harrison 2003).

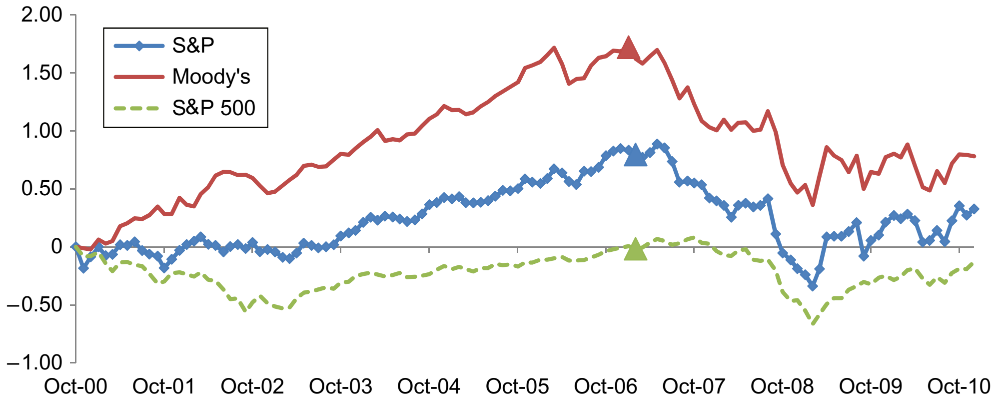
5. Robustness Checks

We conduct several robustness tests to verify our empirical results.

5.1. Measurement of Tone—Naïve Bayesian Approach

Prior research indicates that textual analysis based on the dictionary approach does not tailor to the need for specific type of disclosures or take into account of the

Figure 1 **(Color online) The Cumulative Returns of Two Credit Rating Agencies**



Notes. This figure plots the cumulative monthly returns of McGraw Hill Financial Inc., which is the holding company of Standard & Poor's, and Moody's Corporation from October 2000 to December 2010. The price of McGraw Hill is the solid blue line with the diamond marker. The price of Moody's is the solid red line. The S&P 500 index is the dotted green line. The data were downloaded from Yahoo! Finance. The tickers for Moody's Corporation, McGraw Hill Financial Inc., and S&P 500 are MCO, MHFI, and ^GSPC, respectively. The triangle markers on each line indicate January 2007.

contextual words in the sentence (Li 2010). To ensure that our results are not vulnerable to the measurement errors in tone, we use the naïve Bayesian algorithm to construct alternative tone measures.

We classify the sentences in each report along two dimensions: tone and content. Tone consists of positive and negative tones. Content reflects the rationales behind rating actions. To determine the classification of contents, we first read through a random sample of rating reports and identify seven categories of rationales used by S&P, including finance and accounting, management, operation, industry, legal, macroeconomics, and others. We then quantify tones conditional on each content category. In our empirical analyses, we replace our original three tone measures (*NET_TONE*, *TONE_NEG*, and *TONE_POS*) by the three naïve Bayesian-derived tone measures (*NET_TONE_NB*, *TONE_NEG_NB*, and *TONE_POS_NB*) and rerun our main tests. We report empirical results in Tables 7 and 8.

Table 7 shows the empirical results supporting Hypothesis 1 are quantitatively and qualitatively similar to those reported in Tables 2–6 when we employ the alternative tone measures. In some cases, we even find stronger results than before. For example, the coefficient on *NET_TONE* in Model 5 in Table 2 is significance at the 5% Level, and the coefficient on *TONE_NEG* in Model 6 is significant at the 10% level. With the naïve Bayesian approach, the coefficients on *NET_TONE_NB* and *NET_NEG_NB* become significant at the 1% level, shown in Models 1 and 2 of Table 7. In predicting future downgrade, Models 5 and 6 in Table 7 show a stronger predictability by *NET_TONE_NB* than the prior results in Table 3. The improvement in our empirical results is also consistent with the results of Li (2010), who argues that the statistical approach can improve the explanatory power of tone.

Table 8 shows similar results in rejecting Hypothesis 2. Panel A shows that all the four incentive variables are significantly and positively related to *NET_TONE_NB* at the 5% significance level. Moreover, all the incentive variables are significantly and positively related to *TONE_NEG_NB* and are significantly and negatively related to *TONE_POS_NB*. In Panel B, we find that the information content of the tone from S&P's perspective (proxied by future downgrade) and investors' perspective (proxied by $CAR(-1, 1)$ is all statistically significant at the 5% significance level regardless of the level of conflict of interest.

Overall, we confirm the robustness of our main results when using alternative tone measures.

5.2. Tone and Content of Credit Rating Action Reports

In the second robustness test, we explore the information content of the tone related to rating rationales. Using the naïve Bayesian algorithms, we can categorize the whole report into seven broad information categories (such as finance- and accounting-related or macroeconomics-related Information, etc.). We first identify the keywords contained in a random sample of 2,000 sentences that fall into each of the seven broad information categories. Then, within each sentence, we further classify the tone of the sentence into positive or negative groups. The algorithms use these sentences as the base to categorize all the sentences in each rating report (see Appendix B for details). We compute *NET_TONE* under each broad category in a credit rating report by subtracting the number of positive sentences from the number of negative sentences and dividing by the total number of the sentences in a report. By splitting the tone into seven categories of information, we can further verify Hypothesis 1. The empirical results are reported in Table 9.

Table 7 Robustness Test: The Information Value of Alternative Tone Measures

Dependent variable	*CAR*(−1, 1)		*DOWNGRADE_YR1*		*DOWNGRADE_YR2*		*CAR*(2, 30)	*CAR*(2, 90)	*CAR*(2, 180)	*CAR*(2, 360)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
NET_TONE_NB	−0.0341***		0.1688***		0.1951***		0.0154	−0.0041	−0.0017	−0.0326
	(−4.01)		(9.27)		(5.88)		(1.32)	(−0.16)	(−0.06)	(−0.88)
TONE_NEG_NB		−0.1067***		0.3057***		0.3209***				
		(−3.98)		(4.08)		(3.81)				
TONE_POS_NB		−0.0508***		−0.0089		−0.0481				
		(−3.79)		(−0.13)		(−0.62)				
UP	−0.0050	−0.0025	−0.0712***	−0.0760***	−0.0620**	−0.0665**	0.0493***	0.0829***	0.0856***	0.0849***
	(−0.85)	(−0.49)	(−3.47)	(−3.54)	(−2.05)	(−2.06)	(5.13)	(3.94)	(2.89)	(3.23)
DOWN	−0.0096	−0.0069	−0.0233	−0.0285	−0.0403	−0.0450	0.0026	0.0092	0.0426	0.0683**
	(−1.17)	(−0.80)	(−0.84)	(−1.02)	(−1.51)	(−1.63)	(0.23)	(0.44)	(1.13)	(1.99)
POSWATCH	−0.0218	−0.0167	−0.1287***	−0.1383***	−0.0794	−0.0882	−0.0159	−0.0324	−0.0251	−0.0400
	(−1.09)	(−0.80)	(−2.71)	(−3.11)	(−1.46)	(−1.64)	(−0.52)	(−0.88)	(−0.47)	(−0.94)
NEGWATCH	−0.0541*	−0.0478	0.2812***	0.2693***	0.2607***	0.2498***	−0.0188	−0.0297	−0.0403	−0.0383
	(−1.77)	(−1.45)	(5.69)	(5.79)	(4.41)	(4.36)	(−0.71)	(−0.65)	(−0.77)	(−0.79)
POSOL	−0.0375*	−0.0190	−0.1224**	−0.1574***	−0.1015*	−0.1337**	−0.0219	−0.0455	−0.0516	−0.0657*
	(−1.95)	(−0.78)	(−2.27)	(−3.17)	(−1.75)	(−2.35)	(−0.87)	(−1.23)	(−1.13)	(−1.70)
NEGOL	−0.0409*	−0.0265	0.0720	0.0448	0.1309**	0.1060*	−0.0199	−0.0457	−0.0494	−0.0679**
	(−1.70)	(−0.93)	(1.44)	(0.94)	(2.12)	(1.71)	(−0.77)	(−1.11)	(−1.07)	(−2.32)
STABLEOL	−0.0375*	−0.0223	−0.0771	−0.1059**	−0.0304	−0.0568	−0.0287	−0.0629*	−0.0739*	−0.1053***
	(−1.89)	(−0.92)	(−1.46)	(−2.16)	(−0.52)	(−0.97)	(−1.11)	(−1.67)	(−1.65)	(−2.60)
FALLEN_ANGEL	−0.0175	−0.0177	0.1177***	0.1179***	0.0816*	0.0818*	−0.0031	−0.0194	−0.0621*	−0.0468*
	(−1.57)	(−1.61)	(2.73)	(2.72)	(1.65)	(1.65)	(−0.27)	(−0.81)	(−1.77)	(−1.68)
RISING_STAR	−0.0080	−0.0067	0.0205	0.0180	0.0081	0.0059	−0.0067	−0.0499**	−0.0366	−0.0217
	(−1.08)	(−0.88)	(0.53)	(0.46)	(0.13)	(0.09)	(−0.62)	(−2.40)	(−1.61)	(−0.68)
RATING_CHANGE	−0.0033	−0.0041	−0.0387***	−0.0371***	−0.0338***	−0.0323***	0.0171**	0.0262**	0.0284*	0.0112
	(−0.83)	(−1.14)	(−7.52)	(−6.62)	(−5.95)	(−5.56)	(2.30)	(2.10)	(1.70)	(0.83)
INITIAL_RATING	−0.0003	−0.0011	−0.0146***	−0.0131***	−0.0199***	−0.0185***	−0.0002	−0.0022	−0.0030	−0.0065***
	(−0.24)	(−0.93)	(−4.31)	(−4.32)	(−3.98)	(−3.85)	(−0.12)	(−0.98)	(−1.16)	(−3.22)
LAST_CHANGE	−0.0024	−0.0013	0.0153	0.0134	0.0203	0.0185	−0.0315***	−0.0461***	−0.0546***	−0.0729***
	(−0.37)	(−0.21)	(1.08)	(0.91)	(0.90)	(0.81)	(−3.47)	(−4.36)	(−3.71)	(−4.12)
SUE	0.0022	0.0018	−0.0298***	−0.0290***	−0.0268***	−0.0261***	0.0131***	0.0261***	0.0347***	0.0357***
	(1.18)	(0.95)	(−5.50)	(−5.26)	(−3.38)	(−3.36)	(5.26)	(3.46)	(4.17)	(3.78)
SIZE	0.0022	0.0016	−0.0167***	−0.0156***	−0.0157*	−0.0146*	−0.0006	−0.0086	−0.0113	−0.0199**
	(1.46)	(1.12)	(−3.01)	(−2.85)	(−1.72)	(−1.70)	(−0.26)	(−1.54)	(−1.62)	(−2.07)
MKTRET	0.0951***	0.0867***	0.1682	0.1841	0.3161	0.3307	−0.0263	−0.1599	0.1391	−0.2193
	(3.42)	(3.04)	(0.56)	(0.61)	(1.27)	(1.34)	(−0.37)	(−0.72)	(0.33)	(−1.16)
Δ*VIX*	0.0052	0.0058	0.0214	0.0202	0.0449**	0.0438**	0.0505*	−0.0133	−0.0174	−0.0850*
	(0.58)	(0.69)	(0.61)	(0.58)	(2.05)	(2.02)	(1.84)	(−0.39)	(−0.25)	(−1.80)
INTERCEPT	0.0486	0.1023**	0.7367***	0.6355***	0.9134***	0.8204***	0.1445**	0.3049***	0.4043**	0.7931***
	(0.77)	(2.05)	(5.38)	(4.52)	(3.92)	(3.95)	(2.53)	(2.59)	(2.28)	(3.67)
N	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041
R^2	0.06	0.07	0.29	0.29	0.23	0.23	0.03	0.04	0.06	0.05

Notes. This table presents the robustness tests when linguistic tone is measured through the naïve Bayesian Approach. The dependent variables are the three-day cumulative abnormal return *CAR*(−1, 1), the future downgrade within one year, the future downgrade within two years, and the cumulative abnormal returns *CAR*(2, 30), *CAR*(2, 60), *CAR*(2, 180), and *CAR*(2, 360), respectively. *NET_TONE_NB* is *TONE_NEG_NB* minus *TONE_POS_NB*. *TONE_POS_NB* is the positive tone computed from the naïve Bayesian approach. *TONE_NEG_NB* is the negative tone computed from the naïve Bayesian approach. All other variables are defined in Appendix C. The t-values are calculated based on robust standard errors clustered by both rating analyst and year. We include year and industry fixed effects.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Models 1–3 of Table 9 employ returns as the dependent variable for the full sample, credit watch subsample, and rating outlook subsample, respectively. We find that *TONE_FA*, which is a proxy for finance- and accounting-related information, is the only variable that is significantly and positively related to the returns at the 5% significance level. These results are intuitive, because the finance and accounting information is the relevant information related to default risk of the rated firm. Models 4–6 use the future rating downgrade in one year as the dependent variable. We find that *TONE_MACRO* is the only variable that is significantly and positively related to future downgrade at the 10% significance level, suggesting that the predicting power of tone for future

Table 8 Robustness Test: Incentives and the Information Value of Tone in the Rating Action Reports

Panel A: The relation between tone and incentives of S&P

Dependent variable	*NET_TONE_NB*				*TONE_NEG_NB*				*TONE_POS_NB*			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
SP_RELATION	0.0222***				0.0095***				−0.0127***			
	(3.78)				(2.64)				(−3.60)			
BOND_SIZE		0.0178***				0.0098***				−0.0080***		
		(4.86)				(4.53)				(−3.15)		
N_{BONDS}			0.0188***				0.0111***				−0.0078**	
			(4.38)				(5.07)				(−2.52)	
D_{2007}				0.0816***				0.0472***				−0.0344***
				(3.28)				(2.85)				(−3.87)
$D_{MISSING}$		0.2576***	0.0398***			0.1461***	0.0283***			−0.1115***	−0.0115	
		(4.90)	(2.74)			(4.75)	(4.18)			(−3.08)	(−1.30)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041	3,041
R^2	0.60	0.60	0.60	0.59	0.47	0.47	0.47	0.46	0.60	0.60	0.60	0.59

Panel B: The information value of the reports and the incentives of S&P

Dependent variable	*DOWNGRADE_YR1*				*CAR*(−1, 1)			
Incentive variable	*SP_RELATION*	*BOND_SIZE*	N_{BONDS}	D_{2007}	*SP_RELATION*	*BOND_SIZE*	N_{BONDS}	D_{2007}
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
[1] *NET_TONE_NB*	0.1413***	0.1807***	0.1784***	0.1739***	−0.0261***	−0.0453***	−0.0370***	−0.0422***
	(3.97)	(3.79)	(4.06)	(6.60)	(−2.89)	(−3.26)	(−2.89)	(−3.97)
[2] *NET_TONE_NB* × *INCENTIVE*	0.0397	−0.0298	−0.0315	−0.0424	−0.0122***	0.0193	−0.0023	0.0120
	(0.90)	(−0.38)	(−0.38)	(−0.93)	(−3.13)	(1.07)	(−0.16)	(0.67)
[3] *INCENTIVE*	−0.4293	0.1688	0.4016	−0.1872	0.0159	−0.1406	−0.0802	0.0443
	(−0.97)	(0.36)	(0.97)	(−1.00)	(0.14)	(−1.31)	(−1.01)	(0.41)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,041	1,985	1,985	3,041	3,041	1,985	1,985	3,041
R^2	0.29	0.30	0.30	0.27	0.07	0.10	0.10	0.07
Coefficient [1] + [2]	0.1810***	0.1509***	0.1469***	0.1316***	−0.0383***	−0.0261**	−0.0393***	−0.0302**
p-value	0.000	0.002	0.004	0.000	0.000	0.021	0.000	0.022

Notes. This table presents the robustness tests when linguistic tone is measured through the naïve Bayesian approach. Panel A shows the determinants of tone by the incentives. The dependent variables are *NET_TONE_NB*, *TONE_POS_NB*, and *TONE_NEG_NB*, which are the net tone, positive tone, and negative tone, respectively, computed from the naïve Bayesian approach. *SP_RELATION* is the natural logarithm of the number of days between the announcement date and the day when S&P first rated the firm. *BOND_SIZE* is the natural logarithm of the total amount outstanding of all the bonds within each firm. N_{BONDS} is the natural logarithm of the number of S&P rated bonds within each firm. D_{2007} is a dummy variable that equals 1 if the release of rating report is in the post-2007 period and 0 otherwise. $D_{MISSING}$ is a dummy variable that equals 1 if there is no outstanding bond being rated by S&P recorded in the Mergent FISD and 0 otherwise. In Panel B, the dependent variables are the dummy variable that takes the value 1 if there is a rating downgrade within one year after the current rating action and 0 otherwise in Models 1–4, and the cumulative abnormal return within the (−1, 1) event window for Models 5–8. The *INCENTIVE* variable takes the value 1 if *SP_RELATION* is greater than the median, *BOND_SIZE* is greater than the median, N_{BONDS} is greater than the median, and D_{2007} equals 1, and 0 otherwise. All other control variables are the same as before in Table 5 and are defined in Appendix C. We have also included all the interaction terms of *INCENTIVE* and the control variables. The *t*-values are calculated based on robust standard errors clustered by year. We also include year and industry fixed effects (except in Models 4, 8, and 12 in Panel A and Models 4 and 8 in Panel B, in which we include only the industry fixed effects).

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

rating change mainly comes from the assessment of the macroeconomics information provided by S&P.

We also conduct additional robustness tests to examine whether our findings are sensitive to other information released concurrently such as stock analyst recommendations and stock analyst earnings forecasts and to the characteristics of credit ratings analysts. Our main results are robust, and these results are available upon requests.

6. Conclusion

In this paper, we test whether credit rating action reports contain new information beyond credit rating actions. We find that linguistic tone—one aspect of qualitative information contained in rating action reports—significantly affects stock returns and predicts future downgrades. These results suggest that the reports contain new default-related information.

Table 9 The Specific Information Content of the Linguistic Tone

Dependent variable	*CAR*(−1, 1)			*DOWNGRADE_YR1*		
Sample	All	Watchlist only	Outlook only	All	Watchlist only	Outlook only
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
TONE_FA	−0.0380***	−0.0944***	−0.0218*	0.1578***	0.1020	0.1552***
	(−2.95)	(−2.87)	(−1.91)	(4.39)	(1.59)	(3.02)
TONE_MGT	0.1410	0.1494	0.1692	0.3597	0.1914	0.4528
	(1.12)	(0.81)	(1.38)	(0.72)	(0.32)	(0.42)
TONE_OR	−0.0269	−0.0769*	−0.0174	0.1439***	0.3030	0.0101
	(−1.38)	(−1.67)	(−0.68)	(4.27)	(1.50)	(0.09)
TONE_IND	−0.0217	0.0639	−0.0158	0.1283	0.6420**	−0.0618
	(−0.76)	(0.66)	(−0.37)	(0.81)	(2.55)	(−0.28)
TONE_LEGAL	−0.4111***	−0.7070***	−0.1220	0.3655	−0.2200	0.7621
	(−3.43)	(−3.06)	(−1.60)	(1.02)	(−0.23)	(1.32)
TONE_MACRO	−0.0227	−0.0095	−0.0172	0.4189***	0.6413**	0.3373*
	(−0.59)	(−0.08)	(−0.35)	(2.97)	(1.99)	(1.75)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
N	3,041	639	1,269	3,041	639	1,269
R^2	0.06	0.15	0.03	0.29	0.38	0.18

Notes. This table presents the relation between the content of tone and the stock market reaction and future downgrade. *TONE_FA* is the number of negative sentences that is related to finance and accounting information minus the positive number of sentences and then divided by the total number of sentences in the reports. *TONE_MGT* is defined in a similar way, where sentences are related to management issues. *TONE_OR* is defined in a similar way where sentences are related to operations of the firm. *TONE_IND* uses the sentences that are related to industry in which the firm belongs to. *TONE_LEGAL* uses the sentences that are related to the legal issues faced by the firm. *TONE_MACRO* uses the sentences that are related to the macroeconomic environment related to the firm. The base group is *OTHER*, tone that does not fall into any of the six specific categories. The tone is computed via the naïve Bayesian approach. Models 1–3 employ the dependent variable as cumulative abnormal return *CAR*(−1, 1). Models 4–6 employ the dependent variable, which is a dummy variable that equals 1 if there is a downgrade in one year after the rating action announcement and 0 otherwise. All other variables are the same as before, which are defined in Appendix C. The *t*-values are calculated based on robust standard errors clustered by both rating analyst and year. We include year and industry fixed effects.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

More importantly, we find that the tone in the rating action reports is not more favorable when S&P faces higher conflict of interest, in contrast to the literature that usually documents rating inflation under high conflict of interest. We also find that the information value of tone is not affected by the conflict of interest.

Our study helps to better understand the information provisional role of CRAs in the context of credit rating action reports. Recently, the SEC adopted new rules to regulate the format and content of the credit rating action reports to improve the transparency of the granting of credit ratings. Our study implies that the stock market looks into the qualitative information released by CRAs and provides direct empirical support for this policy movement. Moreover, we find that CRAs are trying to validate the information in the rating reports by consistent future rating actions. A more careful reading of these credit rating action reports can be fruitful for both investors and regulators to accurately evaluate CRAs' assessments of a firm's default risk.

Acknowledgments

The authors are very grateful to department editor Wei Jiang and two anonymous reviewers for helpful and constructive comments and suggestions that greatly improved this paper. They thank Craig Brown, Souphala Chomsisengphet, Jess Cornaggia, Jin-Chuan Duan, David Hirshleifer, Byoung-Hyoun Hwang, Zsuzsa Huszar, Ravi Jain, Pepa Kraft, Robert Kimmel, Hon Sing Lee, Xiaohong Liu, Vikram Nanda, Marco Pagano, Nagpurnanand Prabhala, Wenlan Qian, David Reeb, Amit Seru, Johan Sulaeman, Dragon Y. Tang, Neng Wang, Xin Wang, Yupana Wiwattanakantang, and Liuren Wu, as well as seminar participants at the National Chengchi University, the National University of Singapore, and the Hong Kong University for comments and suggestions. The authors also thank Geoffrey Sim Kian Ju and Kenny Teo Xing Da for their excellent research assistance. Financial support from the National Chengchi University and the National University of Singapore is greatly acknowledged. This study received an academic award sponsored by the E. SUN Bank in Taiwan. All remaining errors are the authors' responsibility.

Appendix A. Samples of Credit Rating Action Reports

This appendix contains two S&P's credit rating reports: "Building Materials Holding Corp. Downgraded to 'BB-', Remaining On CreditWatch Negative" by Pamela Rice and Andy Sookram, published on November 20, 2007, by Standard & Poor's Financial Services LLC; and "Xerox Corp. Corporate Credit Rating Raised to 'BBB'; Off CreditWatch; Outlook Is Stable" by Martha Toll-Reed, published on April 21, 2008, by Standard & Poor's Financial Services

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A.1. Rating Downgrade

Building Materials Holding Corp. Downgraded To "BB-", Remaining On CreditWatch Negative

Primary Credit Analyst:

Pamela Rice, New York (1) 212-438-7939; pamela_rice@standardandpoors.com.

Rationale. On Nov. 20, 2007, Standard & Poor's Ratings Services lowered its corporate credit rating on San Francisco-based Building Materials Holding Corp. (BMHC) to "BB−" from "BB" and its senior secured bank loan rating to "BB" from "BB+". The ratings remain on CreditWatch with negative implications where they were placed on Oct. 18, 2007, following a change-of-management initiative by Chapman Capital LLC, BMHC's largest shareholder.

The downgrade reflects the ongoing weakness in the U.S. housing industry and our expectation that this downturn will last longer than previously expected. Given BMHC's exposure to residential construction, this trend has hurt, and will continue to hurt, the company's operating performance. As a result, its consolidated credit measures have deteriorated in 2007, reaching levels that are inconsistent with the former ratings. Although the company has substantial availability under its revolving credit facility, its ability to meet its financial covenants over the next few quarters could be challenged, given our expectations that markets will decline further in 2008.

Chapman Capital announced in October that it was seeking to replace BMHC's chairman and CEO, Robert Mellor, with Stanley Wilson, president of BMHC subsidiary BMC West Corp. Should this change occur, it could lead to unexpected changes in business strategies that are neither supportive of credit quality nor within our expectations for the current ratings on BMHC.

We will watch for the outcome of this shareholder action. We will also discuss with management its business and financial outlook, considering the continued downturn in the housing market. We could lower the ratings if the actions BMHC is taking to weather the downturn do not begin to stabilize financial results or if liquidity becomes an issue.

Summary. Positive tone: 0.0028; negative tone: 0.0270.

A.2. Rating Upgrade

Xerox Corp. Corporate Credit Rating Raised To "BBB"; Off CreditWatch; Outlook Is Stable

Primary Credit Analyst:

Martha Toll-Reed, New York (1) 212-438-7867; molly_toll-reed@standardandpoors.com.

Rationale. On April 21, 2008, Standard & Poor's Ratings Services raised its corporate credit rating on Norwalk, Conn.-based Xerox Corp. to "BBB" from "BBB-". The upgrade reflects the company's pending securities lawsuit settlement, which removes a material financial uncertainty; strong annual free operating cash flow; and our expectation that Xerox will maintain a stable, moderately leveraged financial profile. At the same time, Standard & Poor's removed the rating from CreditWatch, where it had been placed with positive implications on March 27, 2008. The outlook is stable.

The ratings reflect Xerox's good position in its core document management business, large base of recurring post-sales revenues, and moderate leverage. These factors are offset partially by mature and highly competitive industry conditions, which are expected to constrain any increase in total revenue.

Xerox is a global company serving the document management markets with revenues totaling \$17.2 billion in 2007. The company's document management activities encompass developing, manufacturing, marketing, servicing, and financing a broad variety of document equipment, software, solutions, and services, including black and white and color copiers and multifunction devices, professional services, document outsourcing, and desktop and production printing. In May 2007, Xerox completed the acquisition of Global Imaging Systems Inc.

We expect Xerox to sustain modest, constant-currency revenue growth in the near to intermediate term, with flat to moderate declines in equipment sales offset by an increase in postsales revenues (about 70% of total revenues). Revenues in the quarter ended March 31, 2008, increased 1%, excluding the impact of currency and the Global acquisition. Adjusted EBITDA levels are expected to remain moderately volatile, particularly on a quarterly basis, driven by our inclusion of restructuring charges in EBITDA, changes in product sales mix, and competitive pricing actions. However, we expect annual adjusted EBITDA margins to remain at 9% to 11%.

Standard & Poor's expects Xerox to maintain a solid, investment-grade financial profile, with adjusted total debt to nonfinancing EBITDA less than 2×. Total debt to EBITDA was 1.5× as of fiscal 2007. Xerox took an aftertax charge of \$491 million in the first quarter of 2008 to cover the litigation settlement and to reserve for other pending cases. We expect Xerox to balance share repurchases, moderate acquisition activity, and pending cash settlement payments with strong annual free operating cash flow and modest incremental debt (adjusted for equipment financing operations).

Liquidity. In the near term, Xerox is expected to have consistent profitability and cash flow generation, and to maintain sufficient sources of liquidity to meet near-term debt maturities. Ongoing cost reductions are expected to largely offset competitive industry pricing conditions. We expect Xerox to generate free operating cash flow (excluding changes in finance receivables) of more than \$1 billion annually. Xerox had cash and short-term investments of more than \$800 million as of March 31, 2008, as well as access to a \$2 billion unsecured revolving credit facility maturing April 30, 2012. Effective April 30, 2008, at least \$1.4 billion of this facility will mature on April 20, 2013, as a result of Xerox's exercise of its right under the facility to extend the maturity date for one year.

Outlook. The outlook is stable, reflecting Xerox's consistent nonfinancing operating performance. Ratings improvement is limited by highly competitive industry conditions, potential exposure to economic weakness, reduced capital spending activity, and modest constant-currency revenue growth (excluding the impact of acquisitions). We could revise the outlook to negative if Xerox sustains a decline in operating profitability as a result of revenue weakness and/or heightened competition, or fails to maintain leverage at less than 2× because of acquisition activity or stepped-up share repurchases.

Summary: Positive tone: 0.0133; negative tone: 0.0102.

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A.3. List of the Top 10 Positive and Negative Words Used in the Rating Reports

Number	Positive words	Negative words
1	Stable	Poor
2	Positive	Negative
3	Strong	Weak
4	Improved	Decline
5	Improve	Concerns
6	Good	Declined
7	Profitability	Weaker
8	Outstanding	Restructuring
9	Leading	Declines
10	Despite	Challenges

Appendix B. Naïve Bayesian Algorithm

In this appendix, we provide a detailed description of our naïve Bayesian machine learning algorithm, including the data preparation process, algorithm training, text classification process, and algorithm accuracy validation.

B.1. Algorithm Basics

Developments in computational linguistics and machine learning algorithms have led to improved textual analysis techniques, of which there exist two general approaches: the rule-based approach (or dictionary approach) and the statistical approach. The dictionary approach uses an algorithm to read a text and classify words (or phrases) into specific categories based on predefined rules (i.e., a dictionary). Examples of such dictionaries include the General Inquirer, developed by Harvard psychologist Philip J. Stone, the Linguistic Inquiry and Word Count software developed by James W. Pennebaker, and the financial sentiment dictionaries developed by Loughran and McDonald (2011). The statistical approach utilizes statistical techniques to infer the context of a text and classify documents based on statistical inference (Manning and Schutze 1999, Mitchell 2006). One example of this approach is the naïve Bayesian algorithm.

Under the naïve Bayesian algorithm, a sentence is first reduced to a list of words, w, with each word weighted by its frequency of occurrence in a sentence. The objective is to classify the sentence into a specific category, c_k, out of a set of k categories, $c \in \{c_1, c_2, \ldots c_k\}$. The algorithm chooses the beset category by solving the following maximum likelihood problem:

$$c^* = \underset{c\in\{c_1,c_2,\ldots,c_k\}}{\arg\max} \frac{P(w \mid c)P(c)}{P(w)}.$$

Since $P(w)$ does not change over the range of categories, it can be eliminated to yield:

$$c^* = \underset{c\in\{c_1,c_2,\ldots,c_k\}}{\arg\max} P(w \mid c)P(c).$$

By applying Bayes' rule and making the "naïve" assumption that the probability of each word appearing in a text is unaffected by the presence of other words in the text (i.e., that given a text's category, the words are conditionally independent), the previous expression is equivalent to

$$c^* = \underset{c\in\{c_1,c_2,\ldots,c_k\}}{\arg\max} P(c)\prod_{j=1}^{n} P(w_j \mid c),$$

where n is the number of words w in the text, and $w \in \{w_1, w_2, \ldots w_j\}$.

The naïve Bayesian algorithm is therefore a prediction model, where the words in a text are the input variables, and the probabilities of each category are the predicted values. The parameters of this prediction model (i.e., the conditional probabilities of the frequency of word occurrence given a category) are learned from a training data set that is manually coded by the researcher. It is hence also known as a machine learning text classification algorithm.

We use the naïve Bayesian algorithm because of its advantages over the dictionary approach. First, the dictionary approach does not take into account the context of a sentence. For example, if the sentence is describing firm earnings, "increase" should be treated as a positive word. However, if the sentence is describing operational costs, then it should be considered a negative word. Second, the naïve Bayesian approach is domain specific. It adapts to words that appear in texts and their probabilistic relation to a certain category. This results in increased classification accuracy for the specific context. Third, the dictionary approach assigns the same weight to all words in the dictionary, whereas the naïve Bayesian approach utilizes the probabilistic relationship between words and categories. The dictionary approach is therefore likely to underperform the naïve Bayesian approach, a result that has been documented by Li (2010). Finally, the dictionary approach relies on ready-built dictionaries, which are not always suitable for the type of text being analyzed. For example, the financial dictionaries developed by Loughran and McDonald (2011) are based on 10-K filings. Although they may be Well suited to analyze corporate reports, they may not be entirely appropriate for credit rating action reports. Furthermore, we aim to conduct text classification along two dimensions involving tone and content categories, which cannot be readily implemented using a dictionary approach.

B.2. Tone and Content Categories

We perform text classification at the sentence level, since a sentence is a natural unit for expressing tone and opinion. Each sentence in each report is classified along two dimensions. The first is tone, which comprises two categories: positive and negative. The second is content, which comprises seven categories based on S&P's justifications for rating actions: finance and accounting, management, operation, industry, legal liability, macroeconomics, and others. The finance and accounting category includes issues such as change in capital structure, violation of bond covenant, share repurchase, dividend payout, change in profitability and performance, cash inflow and outflow, earnings restatement, and internal control effectiveness. The management category consists of change of CEO and management team, change of ownership structure, and change of directors. The operation category covers customer and supplier relationship, asset divesture, technology advancement, and relocation of capacity. The industry category includes industry competition and market position. The legal liability category contains potential or current lawsuits with investors and customers, or patents. The macroeconomic category covers changes in macroeconomic condition such as interest rate change, fluctuation of oil price, regulatory change, and market sentiment. The "others'' category acts as a catchall for descriptive sentences with little information content on rating rationales.

B.3. Data Preparation

We first download credit rating action reports from the Standard & Poor's RatingsDirect portal for 1998 to 2010. We then remove the headers, footers, regulatory disclosures, and disclaimers before performing textual analysis since these sections are typically not processed by investors and do not contain any tone or opinions.

B.4. Algorithm Training and Text Classification

Our naïve Bayesian algorithm is coded in Perl. We implement stemming and stopwording processes prior to training and using the classifier. Stemming is the process of reducing inflected or derived words to their base or root form (e.g., "dependent" to "depend") to increase the power of textual analysis. Stopwording is the process of removing stopwords from a sentence. Stopwords are a class of words that are typically the short, frequently occurring words in a language. They include articles, case particles, conjunctions, pronouns, auxiliary verbs, and common prepositions, and usually have only a grammatical function within a sentence and do not add meaning. Some examples of stopwords for the English language are "the," "and," "it," "is," and "of." These processes are performed using the Lingua::Stem::En and Lingua::EN::Stopwords modules in Perl. The sentences are then converted into hash variables and fed into the Algorithm::NaïveBayes module to train the classifier. The trained classifier is then used to predict the tone and content categories of all sentences in our sample of credit rating action reports.

Appendix C. Definitions of Variables

UP	=	Dummy variable that equals 1 if an upgrade and 0 otherwise
DOWN	=	Dummy variable that equals 1 if a downgrade and 0 otherwise
NEGWATCH	=	Dummy variable that equals 1 if a negative credit watch action and 0 otherwise
POSWATCH	=	Dummy variable that equals 1 if a positive credit watch action and 0 otherwise
NEGOL	=	Dummy variable that equals 1 if a negative outlook action and 0 otherwise
POSOL	=	Dummy variable that equals 1 if a positive outlook action and 0 otherwise
STABLEOL	=	Dummy variable that equals 1 if a stable outlook action and 0 otherwise
$CAR(-1, 1)$	=	Cumulative abnormal return over a three-day window surrounding the event date of rating action
NET_TONE	=	The negative tone minus positive tone
NEG	=	The percentage of negative words divided by the total number of words in the report
POS	=	The percentage of positive words divided by the total number of words in the report
FALLEN_ANGEL	=	Dummy variable that equals 1 when a rating changes from investment grade to speculative grade and 0 otherwise
RISING_STAR	=	Dummy variable that equals 1 when a rating changes from speculative grade to investment grade and 0 otherwise
RATING_CHANGE	=	The magnitude of rating change, as measured by the number of grades that a rating is changed
INITIAL_RATING	=	The scaled credit rating before rating action announcement: AAA is converted to 1; AA+, AA, and AA− are converted to 2, 3, and 4; A+, A, and A− are converted to 5, 6, and 7; BBB+, BBB, and BBB− are converted to 8, 9 and 10; BB+, BB, and BB− are converted to 11, 12, and 13; B+, B, and B− are converted to 14, 15, and 16; CCC+, CCC, and CCC− are converted to 17, 18, and 19; CC, C, and D are converted to 20, 21, and 22
LAST_CHANGE	=	The number of days between the last and current rating actions, as measured by the natural logarithm of the number of days between the last and current rating actions by S&P
SUE	=	The standardized unexpected earnings, as measured by the difference between earnings at quarter t and earnings at quarter $t-4$, normalized by the standard deviation of earnings surprises over the past eight quarters
SIZE	=	The market value of the firm, as measured by the natural logarithm of the market value of equity in the month before the month of the rating action
MKTRET	=	The monthly value-weighted stock market return from CRSP before the rating action day
ΔVIX	=	The change of options exchange market volatility index, measured as the difference of the Chicago Board Options Exchange volatility index (VIX) between the last and current month of the rating action

Appendix C. (Continued)

DOWNGRADE_YR1	=	Dummy variable that equals 1 if there is a downgrade within one year after the current rating action and 0 otherwise
DOWNGRADE_YR2	=	Dummy variable that equals 1 if there is a downgrade within two years after the current rating action and 0 otherwise
SP_HISTORY	=	S&P and client relationship, as measured by the natural logarithm of the number of calendar days between the day when S&P first rated the firm to the day when the rating report on the firm was released
BOND_SIZE	=	Bond size, as measured by the natural logarithm of the total amount of bonds outstanding within a firm recorded in the Mergent FISD
N_{BONDS}	=	Number of bond issues, as measured by the natural logarithm of the number of S&P rated bonds within each firm if such bonds exist in the Mergent FISD
D_{2007}	=	Dummy variable that equals 1 if the release of the credit rating report is in the post-2007 period and 0 otherwise
NET_TONE_NB	=	The negative tone minus the positive tone according to the naïve Bayesian approach
NEG_NB	=	The percentage of negative words according to the naïve Bayesian approach divided by the total number of words in the report
POS_NB	=	The percentage of positive words according to the naïve Bayesian approach divided by the total number of words in the report
TONE_FA	=	The negative tone minus the positive tone under the finance and accounting content category according to the naïve Bayesian approach
TONE_MGT	=	The negative tone minus the positive tone under the management content category according to the naïve Bayesian approach
TONE_OR	=	The negative tone minus the positive tone under the operation content category according to the naïve Bayesian approach
TONE_IND	=	The negative tone minus the positive tone under the industry content category according to the naïve Bayesian approach
TONE_LEGAL	=	The negative tone minus the positive tone under the legal content category according to the naïve Bayesian approach
TONE_MACRO	=	The negative tone minus the positive tone under the macroeconomics content category according to the naïve Bayesian approach

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