Dissecting the Information Value of Sovereign Credit Rating Reports

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ABSTRACT

We dissect the information content of sovereign credit rating reports issued by Moody's in 62 countries for the period 2003–2013. Using the Naïve Bayesian machine learning algorithm, we classify all sentences in each report into positive and negative tone, as well as six informational categories. We find that the negative tone related to "debt dynamics" affected sovereign credit default swap (CDS) spreads the most, indicating Moody's specific skill in assessing sovereign credit risk. Moreover, we use a dozen conventional country-level default predictors to separate the tone of each report into "predicted" and "surprise" tone. We find that the negative "surprise" tone caused a bigger market reaction while the negative "predicted" tone is superior in predicting a future downgrade, reflecting different aspects of credit risk assessment. Using the 2009 Eurozone debt crisis as a natural experiment, we find that public confidence in Moody's financial risk assessment dropped after the crisis afterward. Overall, our study provides new evidence that sovereign credit rating reports contain valuable credit-related information beyond sovereign rating actions.

JEL Classification: F3, E6, G2

Keywords: Eurozone Sovereign Debt Crisis, Naïve Bayesian machine learning algorithm, Sovereign credit default swaps, Sovereign credit rating reports

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1. INTRODUCTION

In recent years, many countries have experienced unprecedented sovereign rating revisions by credit rating agencies (CRAs). In April 2011, Standard & Poor's (S&P) downgraded U.S. sovereign debt from AAA to AA+ for the first time in history, while Moody's and Fitch changed their outlook to negative by the end of 2011. The downgrade attracted a large amount of media coverage, and two years later S&P was sued by several state governments and the federal government for inflating ratings on the subprime mortgage bonds; the agency paid $1.5 billion to settle the lawsuits in 2015 (Bloomberg, 4 February 2015). Similarly, S&P downgraded Italy's sovereign rating in September 2011, followed by Moody's and Fitch. The Italian government was upset about these downgrades and suggested that the country's history, art, and landscape should be considered in any sovereign risk assessment (Financial Times, 4 October 2015). Despite the fact that CRAs often face public scrutiny when they change countries' sovereign credit ratings, there is a dearth of literature examining the quality of CRAs in assessing sovereign credit risk.[5] Our study aims to fill this void by dissecting the information content embedded in Moody's sovereign credit rating reports.

Exploring sovereign credit rating reports is interesting for three reasons. First, the literature on CRAs has focused predominantly on the link between credit rating actions and conflicts of interest (e.g., Griffin and Tang, 2012; Griffin, Nickerson, and Tang, 2013; Kisgen and Strahan, 2010; He, Qian, and Strahan, 2012). Agarwal, Chen, and Zhang (2016) are among the first to directly employ corporate credit rating reports and perform the textual analysis to investigate the conflicts of interest on the part of Standard & Poor's. Their results indicated that the tone of a report does not seem to be inflated by the conventional proxies for conflicts of interest. In the sovereign setting, this concern would be even less severe because CRAs sometimes receive no direct compensation for sovereign credit rating actions (Moody's, 2013). The incentives of issuing sovereign ratings can be more complex than corporate ratings as Gibert (2016) found that unsolicited sovereign ratings were higher than solicited sovereign ratings whereas the opposite is true for corporate ratings (e.g., Fulghieri, Strobl, and Xia, 2013). Therefore, our

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[5] The literature has usually focused on the significant financial market reactions and economic consequences after sovereign rating changes. For example, Brooks, Faff, Hillier, and Hillier (2004) examined the equity market reaction to sovereign credit rating actions; Reisen and von Maltzan (1999) and Ismailescu and Kazemi (2010) studied the effects of credit ratings on sovereign bond yields (CDS spreads). Other studies have examined the information leakage of sovereign credit rating changes prior to sovereign rating change announcements (Michaelides, Milidonis, Nishiotis, and Papakyriakou, 2015), spillover effects of sovereign credit rating changes (Gande and Parsley, 2005; Ferreira and Gamma, 2007), and the effect of a ceiling policy of sovereign credit ratings on corporate decisions (Almeida, Cunha, Ferreira and Restrepo, 2017).

study will focus more on the reputational concern of CRAs in supplying sovereign credit rating reports, and particularly when they change a rating.

Second, the literature on sovereign credit rating actions has revealed that there is limited market reaction to sovereign rating actions, mostly because the information is often leaked before the rating appears officially (e.g., Afonso, Furceri, and Gomes, 2012). Moreover, many information sources used by CRAs in assessing sovereign credit risk are in the public domain (Moody's, 2013). Hence, sovereign credit rating actions can carry little new information compared to those in the corporate settings, in which private information about the rated firm is gathered in the rating process (e.g., Löffler, Norden, and Rieber, 2018). Hence, it is not obvious whether sovereign credit rating reports would be valuable to investors though Agarwal et al. (2016) found that corporate rating reports contained new information.

Third, the economic consequences of sovereign credit rating changes can be more significant than firm-level rating actions because the sovereign ratings affect the efficiency and stability of capital markets within and across countries. For example, Almeida, Cunha, Ferreira, and Restrepo (2014) have demonstrated the real effects of sovereign credit rating actions on firms' financing activities. Hence, if sovereign credit rating reports do contain new information beyond sovereign credit rating actions, they should be taken into account by investors and firm managers in making investment and financing decisions.

The main sample used in this study is Moody's sovereign credit rating reports, which were contemporaneously released with rating actions from 2003 to 2013 for 62 countries (see Table A2). These reports contain detailed information and explain the rationale for the rating actions.[6] To dissect the credit-related information in the sovereign rating reports, we employ a Naïve Bayesian machine learning algorithm to classify, first, all sentences in each report as positive, negative, or neutral in tone.[7] Second, we classify each sentence into one of six content categories (i.e., macroeconomic, public & external finance, debt dynamics, financial sector, political & institutional, and others). These content categories are defined according to the published sovereign credit rating methodologies used by Moody's (2013), Fitch (2011), and

[6] Two sample sovereign rating reports can be found in Appendix B.

[7] Note that our tone variables here (positive, negative, and neutral) are different from those in the literature that usually count the percentage of positive, negative, or neutral words as a share of the total number of words in a report, according to a dictionary approach (Tetlock, 2007; Loughran and McDonald, 2011). We define tone as the percentage of positive, negative, and neutral sentences as a share of the total number of sentences in the sovereign rating report using the Naïve Bayesian algorithm. Such methodology is also used by Agarwal et al. (2016) in their robustness tests for corporate rating reports. Nevertheless, we have employed different information content categories for sovereign rating reports here.

Standard & Poor's (2011). The third dissection is done by separating the overall positive and negative tone of each report into "predicted" and "surprise" components using lagged macroeconomic indicators as the predictors. This separation is necessary to validate the unique information value contained in the rating reports, as Afonso et al. (2012) showed that when the market became more aware of macroeconomic indicators a subsequent sovereign downgrade was not surprising.

For dependent variables, we use the sovereign credit default swap (CDS) spreads as the primary financial instrument to capture the magnitude of the dissected information value because they have standardized contract terms (Li, Li, and Yang, 2017). We also use future downgrades over a one-year time horizon as an alternative instrument to measure the accuracy of credit risk information provided by Moody's.

Our first result reveals that credit rating reports contain more granular credit-related information than credit rating changes. When we put both the credit rating changes and tone variables in the same regression, we find that a negative tone overshadows the rating downgrade in affecting CDS spreads and predicting future rating downgrades. Specifically, a one-standard-deviation increase in negative tone results in a 2.83 basis point (bps) increase in abnormal CDS spreads within the 3-day event window. The spread reaction to negative tone is more economically significant than the reaction to a downgrade, which is 1.37 bps.[8] In predicting future downgrades over a one-year time horizon, a one-standard-deviation increase in negative tone can lead to an increase in downgrade probability of 11.2% to 19.1%. As far as we know, our study is among the first to document the information value of sovereign credit rating reports.

To further validate our findings, we employ a dozen macroeconomic variables that were used in the literature to predict sovereign default risk and build a prediction model for the tone used in the sovereign rating reports. In this way, we are able to separate the tone into the "predicted" and "surprise" subcomponents. We test the relationship between the "predicted" and "surprise" tone and the CDS spreads as well as future downgrades. We find that a negative "surprise" tone is more important in affecting CDS spreads, and a negative "predicted" tone is more powerful in predicting future downgrades. While the latter result corroborates the claims

[8] Although the increase here may look small, it captures the change in the abnormal CDS spread.

made by Afonso et al. (2012), the prior result reveals that the "surprise" component in the reports also provides new credit-related information.

Our second main result provides insights on the relative importance of different types of credit information contained in these reports. Among the six categories of information content, we find that a negative tone associated with "debt dynamics" is most significantly related to abnormal CDS spreads. A one-standard-deviation increase in the negative "debt dynamics" tone leads to a 1.97 bps increase in abnormal CDS spreads within the 3-day event window. This result indicates that Moody's possesses specific skill in analyzing sovereign debt conditions for a sovereign rating action. This finding also corroborates the claim made by Moody's (2013) that it employed in-house analysis to assess a country's sovereign debt condition when assigning sovereign credit ratings. This result tells us what type of information provided by CRAs is the most valuable and useful to international investors.

Our third main result informs on the time-varying nature of the information value of the sovereign rating reports. Since our sample spanned the 2009 Eurozone sovereign debt crisis, we use it as a natural experiment to evaluate whether there is any change in the response to sovereign credit risk assessments made by Moody's before and after the crisis. Indeed, we find a significant decrease in the market reaction to negative tone about the "financial sector" after the crisis. This result suggests a loss of investor confidence in Moody's risk assessments of financial risk, one aspect of sovereign credit risk. Such a reputation loss should be alarming to CRAs because their role in providing information about the credit market relies on public trust and confidence.

We also conducted additional robustness tests by expanding our report sample (i.e., N = 166 reports with rating changes) to include those reports with watchlist and outlook actions only (N = 323 reports with or without rating changes). All our results remain robust in the expanded sample. In our main analysis, we keep the main sample of 166 reports because rating changes are more economically significant than other rating actions.

Our study makes three distinctive contributions to the literature. First, we provide novel evidence that sovereign credit rating reports contain valuable credit-related information. Investors can employ sovereign credit rating reports as an additional source of information to assess credit risk at the country level. This finding extends the sovereign debt literature that examines the economic impact of sovereign ratings on capital markets (Brooks, Faff, Hillier, and Hillier, 2004; Ismailescu and Kazemi, 2010; Afonso et al., 2012).

Second, our study uses the Naïve Bayesian machine learning algorithm to extract different types of information from the rating reports and analyze their economic value and impact. This adds to the literature that employs textual analysis to measure and quantify individual economic behavior and output (e.g., Da, Engelberg, and Gao, 2011; 2015). Our results show that the most informative tone is related to negative debt dynamics; the credit market reacts little to financial sector related tone after the 2009 euro debt crisis. These results provide new evidence on the time dynamics of the informational role of CRAs for sovereign credit risk assessment.

Last, our study provides empirical support for the latest movements made by regulators and policymakers in Europe and the U.S. who aim to enhance the transparency and quality of sovereign credit ratings.[9] Although the literature has provided mixed views of the informational role played by CRAs in sovereign credit ratings, our findings indicate that investors react to more than rating changes in the sovereign credit rating reports. For this reason, there should be specific regulatory guidelines for CRAs to produce more refined credit-related information in the sovereign rating reports, a channel through which CRAs demonstrate the expertise, accountability, and rigor of their rating decisions.

The remainder of the paper is organized as follows. Section 2 reviews the literature and lays out our research methodology. Section 3 describes the data and constructs the key variables. Section 4 presents our main results, and section 5 presents the robustness tests. Section 6 concludes.

2. LITERATURE REVIEW AND RESEARCH METHODOLOGY

Sovereign creditworthiness is at the apex of all ratings within a country's jurisdiction (which include corporate ratings, structural product ratings, municipal ratings, and many more). Government bond yields often serve as the "zero-risk return" benchmark against which all other types of investment returns are measured (Bhatia, 2012). The literature has examined the rating of corporate bonds, structured debt instruments, and mortgage-backed securities, but

[9] For example, the European Securities and Markets Authority (ESMA) instituted several regulations on sovereign credit ratings after identifying various problems with the rating process, including independence, confidentiality of rating information, timing of publication of rating actions, and resources allocated to conduct sovereign credit ratings (ESMA, 2013). For example, Regulation (EU) No 462/2013 (45) requires the disclosure of the key elements underlying rating decisions when publishing sovereign credit ratings. U.S. regulators have also implemented new regulations and reforms to improve transparency in the credit rating process and enhance CRAs' accountability. For example, new regulations are included in the 2006 Credit Rating Agency Reform Act, Section 932 of the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act, and in Securities and Exchange Commission (SEC) Rule 2011and 2014.

very few studies have looked at the quality of sovereign credit ratings (e.g., Afonso et al., 2012). One major contentious issue associated with credit rating agencies is the conflict of interest between CRAs and those who pay for the rating services. Also, because some sovereign ratings are provided by CRAs free-of-charge, there are fewer "revolving-door" issues with the sovereign credit rating analysts. There is much more public scrutiny paid to whether CRAs have exercised due diligence in assessing sovereign risk. These issues lead to an interesting research question: Do CRAs produce high-quality (or informative) risk assessments in the sovereign setting?[10]

The extant literature has focused mainly on the information value of sovereign credit rating actions. For example, Cantor and Packer (1996) and Reisen and von Maltzan (1999) have found significant market reaction to sovereign credit rating changes in the sovereign bond market, whereas Ismailescu and Kazemi (2010), Kiff, Nowak, and Schumacher (2012) and Afonso et al. (2012) document a significant market reaction to rating changes in sovereign CDS markets. But it is not immediately obvious to us what the quality of information provided by CRAs is in assigning sovereign credit ratings. A large amount of information used to assess sovereign credit risk is usually gathered or obtained from public information sources. For example, Moody's Sovereign Credit Rating Methodology published in September 2013 explicitly states that "*(t)he information used in assessing the sub-factors is generally drawn from a number of international sources, including the International Monetary Fund, the Organization for Economic Cooperation and Development, the European Commission, the World Bank, and the Bank for International Settlements"* (page 4). Hence, it is unclear ex ante whether CRAs do more than put the public information together when they assess sovereign credit risk.

As industry practice, CRAs provide sovereign rating reports during credit rating announcements and do not charge an additional fee to produce and disseminate these reports.[11] To evaluate the quality of CRAs' assessment of sovereign credit risk, we use textual analysis to dissect the detailed information contained in these sovereign rating reports.

The most common types of documents that are decoded using textual analysis are newspaper articles (Tetlock, 2007), corporate filings (Kothari, Li and Short, 2009), analyst reports (Huang, Zang and Zheng, 2014), and corporate credit rating reports (Agarwal et al.,

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[10] Appendix B provides two sample sovereign rating reports.
[11] Moody's and Fitch release these sovereign reports via their websites for free. Standard & Poor's charges a fee for the public to access to these sovereign rating reports.

2016). Some recent studies have also employed the Naïve Bayesian machine learning approach to code other types of detailed information from these documents (e.g., Guo, Shi, and Tu, 2016).

In our analysis, we first classify the tone of each report by measuring the number of positive, negative, and neutral sentences as a percentage of the total number of sentences. We use the Naïve Bayesian machine learning approach because we first need to train the algorithm using a large quantity of sentences that are assigned to the positive, negative, and neutral categories. This approach is different from the traditional dictionary approach to textual analysis, which uses a list of positive, negative, and neutral words to classify the tone of each document (Tetlock, 2007; Loughran and McDonald, 2011).[12]

Next, we train the algorithm to classify each sentence in the rating reports into specific information categories. This classification is intuitive, since CRAs usually provide a rationale to justify the ratings in their reports, which address a range of topics, from macroeconomic fundamentals, public and external finances, to political and institutional risk (Gaillard, 2013). Following the sovereign rating methodologies issued by Moody's (2013), Fitch (2011), and Standard & Poor's (2011), and information provided by International Monetary Fund (2010), we specify six categories of information: 1) macroeconomic; 2) public & external finance; 3) debt dynamics; 4) financial sector; 5) political & institutional; and 6) others. We provide detailed explanations of these six information categories in Table C1 in Appendix C. We also categorize each sentence as positive, negative, or neutral in one of the six information categories.

Given that the literature has shown that many macroeconomic variables affect sovereign default risk (e.g., Oura and Valckx, 2013; Maltritz and Molchanov, 2013), we also take into account these predictors when evaluating the sovereign rating reports. The usual default predictors include the recent default history of the country, economic growth, country debt level, and others. We employ these predictors to further decompose the tone information in the sovereign credit rating reports into two components: "predicted" and "surprise." This decomposition allows us to separately evaluate the information value of each report conditional on the default predictors. As Afonso et al. (2012) showed, that the market has become more

[12] We also used alternative tone variables defined in words in robustness tests, and our findings are similar. The results are available upon request. Since our focus in this paper is to identify the specific information content of the rating reports, we use the sentence-defined tone variables, consistent with our research methodology.

aware of macroeconomic indicators and subsequent sovereign downgrades is not completely surprising given the prevalence of information linkage. We therefore examine whether the "surprise" tone in the rating reports is still valuable to sovereign CDS markets.

Last, the 2009 Eurozone sovereign debt crisis was a significant event for sovereign credit ratings because it was the first time the three major CRAs massively downgraded several European countries including Greece, Portugal, Ireland, Spain and Cyprus due to their inability to pay off government debt. Some of these sovereign governments even threatened to launch lawsuits against the CRAs after being downgraded, claiming the assessments were "unfair". We therefore also investigate whether the information value of these sovereign rating reports changed after the crisis.

3. DATA AND KEY VARIABLES

In this section, we explain how we used the Naïve Bayesian machine learning algorithm to measure the tone and the information content of sovereign rating reports. We also present the summary statistics of the key variables.

3.1 Dissection of Sovereign Credit Rating Reports

The Naïve Bayesian machine learning algorithm is a textual analysis technique that classifies sentences into a set of pre-defined categories.[13] In the main tests, we classify the tone and content dimensions of 6,038 sentences in 166 credit rating reports. In the robustness tests, we also include68 reports on watchlist actions (which may also include outlook actions) and 89 reports on rating outlooks only, resulting in a total sample of 323 reports with 10,278 sentences. Tone comprises three categories: positive (POS), negative (NEG), and neutral. The positive (negative) tone is the percentage of positive (negative) sentences in each report. The neutral tone is the percentage of sentences that are neither positive nor negative. Overall, 30.3% of sentences in all 323 rating actions reports are classified as positive and 50.9% as negative.

Figure 1 presents the mean net tone scores for three types of rating actions: credit rating changes, watchlists, and outlooks. The net tone is the difference between positive tone (POS) and negative tone (NEG). It is not surprising that upgrade reports have positive net tone, and downgrade reports have negative net tone. The differences in net tone among the three different rating actions (i.e., rating changes, watchlists, and outlooks) are small. The numerical

[13] A more detailed description of our algorithm is provided in Appendix C.

breakdowns of the positive and negative tone for each type of rating action are shown in Panel C of Appendix Table C2.

[Insert Figure 1 about here]

Figure 2 shows the time variation of the net tone in 166 Moody's credit rating reports throughout our sample period. It shows a declining trend in the net tone over time, especially after 2009, which corresponds with the onset of the Eurozone debt crisis.

[Insert Figure 2 about here]

We also classify the content of the reports into six categories, as mentioned above. Each content category has a continuous tone score (between 0 and 1), which is defined as the ratio of sentences classified in a particular content category to the total sentences in a report. The top three types of information content (excluding "others") are macroeconomic (MACRO), public & external finance (PEF), and debt dynamics (DEBT), which constitute 35.7%, 11.4%, and 18.1% of all sentences, respectively, as shown in Panel C of Table C2 in Appendix C.

We also use the algorithm to compute the positive and negative tone in each content category, CONTENT_POS and CONTENT_NEG, where CONTENT represents each of five categories of information respectively (excluding "others"). For each content category, we also calculate the residual positive and negative tone (i.e., POS_RES and NEG_RES) in the report after removing the tone related to that specific content category (i.e., POS_RES = POS – CONTENT_POS and NEG_RES = NEG – CONTENT_NEG). The separation allows us to compare the relative importance of each content category with the remaining content in a rating report.

To separate the positive or negative tone into "predicted" and "surprise" components, we employ a prediction model that includes a dozen fundamental determinants of sovereign default risk from the literature (e.g., Oura and Valckx, 2013; Maltritz and Molchanov, 2013). These variables include: the initial sovereign rating before the rating change (INITIAL_RATING); a dummy variable that equals one if a credit rating has been at or close to default (defined as Caa1 and below on Moody's rating scale) within the past two years and zero otherwise (RECENT_DEFAULT); the annual real GDP growth of the sovereign for the year prior to the current rating action (GDP_GROWTH); the debt-to-GDP ratio of the sovereign for the year prior to the current rating action (DEBT_GDP); the ratio of foreign reserves to GDP of the sovereign for the year prior to the current rating action (FRES_GDP); the annual foreign reserves growth of the sovereign for the year prior to the current rating action

(FRES_GROWTH); the annual percentage change in the exchange rate of the local currency against the dollar for the year prior to the current rating action (FX_GROWTH); the ratio of the trade balance to GDP of the sovereign for the year prior to the current rating action (TRADEBAL_GDP); the monthly return of the S&P 500 index for the month prior to the current rating action (SP500); a sub-index of the Index of Economic Freedom in the World provided by the Heritage Foundation that describes a country's governance practices related to fiscal practices and the tax burden (FISCAL_FREEDOM); a sub-index of the Index of Economic Freedom in the World provided by the Heritage Foundation that describes a country's governance practices related to price stability and price controls (MONETARY_FREEDOM); a sub-index of the Index of Economic Freedom in the World provided by the Heritage Foundation that describes the independence and efficiency of a country's financial sector (FINANCIAL_FREEDOM); and an indicator of a high market stress period (HIGH_STRESS), measured by the probability that the VIX index is in a high-volatility state (out of three possible states), estimated using a Markov regime-switching framework as described in Hamilton and Susmel (1994) and Gonzalez-Hermosillo and Hesse (2011). The detailed definitions of these country-level default predictors are given in Table A1.

3.2 Definitions of Key Variables

Percentage Changes in the Cumulative Abnormal Sovereign CDS Spread

Our key dependent variable is the percentage change in the cumulative abnormal CDS spread (CDS), summed over the 3-day event window [-1, 1]. A key advantage of using sovereign CDS spread over sovereign debt spread is that the former provides a much more direct measure of sovereign credit risk, since the latter is driven not only by sovereign credit risk, but also by interest rates, changes in supply of the underlying bonds, and illiquidity effects in debt prices (Ang and Longstaff, 2013). Daily CDS mid-spread quotes for the 62 countries in our sample from 2003 to 2013 were obtained from Thomson Reuters Datastream. The list of countries is presented in Appendix Table A2. We focus on U.S. dollar-denominated contracts on senior-tier debt with 5-year maturities, since they are the most conventional contract types. We use euro-denominated contracts when U.S. dollar-denominated contracts were unavailable.

We use a market model adapted from Hull, Predescu, and White (2004), Norden and Weber (2004), and Ismailescu and Kazemi (2010) to calculate the percentage changes in the cumulative abnormal CDS spread. This market model accounts for changes in global market conditions, comovements in regional and global CDS spreads, and sovereign risk spillover and contagion (Gande and Parsley, 2005; Longstaff, Pan, Pedersen, and Singleton, 2011). Specifically, for each event country, we construct two CDS market indices that are equally weighted cross-sectional averages of the CDS spreads for all non-event countries in our sample in two rating classes: investment grade and speculative grade. The daily percentage change in abnormal CDS spread is the percentage change for the event country less the percentage change in the market index corresponding to the same rating status of the event country:

$$CDS_k(t-1,t) = \frac{CDS_{k,t} - CDS_{k,t-1}}{CDS_{k,t-1}} - \frac{I_{k,t} - I_{k,t-1}}{I_{k,t-1}},$$

where $CDS_{k,t}$ is the CDS spread of event country k at time t, and $I_{k,t}$ is the equally weighted CDS market index for all non-event countries with the same rating status excluding event country k at time t. The percentage change in the cumulative abnormal CDS spread over the 3-day event window, CDS(-1,1), is then computed as the sum of the daily percentage change in the abnormal CDS spread. We also construct six post-event cumulative abnormal CDS spread percentage changes: CDS(1,10), CDS(1,20), CDS(1,30), CDS(1,45), CDS(1,60) and CDS(1,90) where 10, 20, 30, 45, 60, and 90 are the respective trading days after the rating action event.

Control Variables

Our control variables for credit rating actions include DOWN, POS_WATCH,[14] NEG_WATCH, POS_OUTLOOK, and NEG_OUTLOOK as rating changes are usually accompanied by watchlist and outlook actions as well. Following Goh and Ederington (1993) and Avramov, Chordia, Jostova, and Philipov (2009), we also include INITIAL_STATUS, RISING_STAR, and FALLEN_ANGEL to capture the initial rating before a rating change and the crossover between speculative and investment grades. Sovereign default risk, as reflected by sovereign CDS spreads, is driven by macroeconomic and global market factors, risk premiums, and liquidity patterns. Following Longstaff et al. (2011) and Kiff, Nowak, and Schumacher (2012), we include a set of control variables to account for changes in sovereign CDS spreads that are not due to credit rating changes or tone. These include the following variables: LOCAL_MKT, which is the MSCI country index return denominated in U.S. dollar; FX_RATE, which is the percentage change in the exchange rate of the local currency against the U.S. dollar; US_MKT, which is the U.S. stock market excess return as the value-weighted

[14] Note that POS_WATCH is not included in the 166 rating change reports because there is no positive watchlist event in these reports. In the sample of 323 reports in the robustness test, this variable is included.

return on all NYSE; AMEX and NASDAQ stocks minus the one-month Treasury-bill return; TREASURY_MKT, which is the change in the five-year constant maturity Treasury rates; VOLRISK_PREM, which is the change in the volatility risk premium as the difference between the VIX index and the realized volatility for the S&P100 index following Garman-Klass (1980); and ADS_INDEX, which is the daily change in the Aruoba-Diebold-Scotti business conditions index. These control variables capture the common factors that drive sovereign credit risk in different countries. Finally, to examine the change in the information value of sovereign credit rating reports after the Eurozone sovereign debt crisis, we include a time dummy variable, POST2009, which equals 1 if the year of the current rating action is after 2009 (i.e., 2010 or later), and 0 otherwise. These variables are defined in Table A1.

3.3 Summary Statistics

Panel A of Table 1 describes our sample selection process. We start with 405 credit rating reports downloaded from Moody's Research & Ratings database for the period 2003–2013. We remove 82 reports that do not have corresponding sovereign CDS data in Datastream. Of the remaining 323 rating action reports, 166 are for credit rating changes (which may include concurrent watchlist or outlook actions), 68 for watchlist actions (which may include concurrent outlook actions), and 89 for outlook actions only. Out of 166 reports with rating changes, 80 reports are for upgrades and 86 are for downgrades.

Table 1 Panel B presents the summary statistics of our key variables in the sample of 166 rating reports.[15] The mean cumulative abnormal CDS spread percentage change CDS(-1,1) is 0.55 bps, consistent with the majority of credit rating changes being downgraded (51.8%). The proportion of downgrades over a one-year time horizon is 21.08%. The mean positive tone and negative tone are 0.3621 and 0.3984 respectively. Table 1 Panel C presents the correlation matrix of our key variables. Positive tone is negatively correlated with downgrade (at -0.86) and "FALLEN_ANGEL" (at -0.21). Negative tone is positively correlated with downgrade (at 0.87) but negatively correlated with "RISING_STAR" (at -0.24).[16] It is not surprising to observe a high correlation between tone variables and rating changes since the reports are required to provide justifications for the rating actions. However, the focus of this study is to see whether the specific content of rating reports reflects the quality of sovereign credit risk

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[15] The summary statistics of the key variables in the extended sample (N = 323) are given in Appendix Table A3.
[16] The correlation coefficient of NEG and DOWN is at 0.61 in the extended sample of 323 rating action reports.

assessments performed by Moody's. Hence, the high correlation between the tone variables and rating changes justifies our use of credit rating reports to answer our research question.

[Insert Table 1 about here]

4. EMPIRICAL FINDINGS

4.1 The Information Value of Sovereign Credit Rating Reports

In this section, we test whether our constructed positive and negative tone (in sentences) based on Naïve Bayesian machine learning algorithm captures the granular default information. We use the percentage change in the cumulative abnormal sovereign CDS spread over the 3-day event window surrounding the announcement date (i.e., CDS(-1,1)) and future downgrades as two testing instruments. Table 2 and Table 3 report the results respectively.

[Insert Table 2 about here]

Models 1 to 3 in Table 2 provide the baseline results, where CDS spread reacts strongly to a sovereign downgrade. Model 2 shows that the abnormal CDS spread change reaction to the downgrade dummy (DOWN) is significant at 2.7 bps. These results are consistent with the literature, which finds that a downgrade induces a greater CDS market reaction than an upgrade (Norden and Weber, 2004; Afonso et al., 2012). In Model 3, we control for other rating actions, such as credit watch and rating outlooks, which are assigned concurrently with the rating changes. The coefficient on DOWN is still statistically significant at the 10% level. The coefficients on the two control variables RISING_STAR and FALLEN_ANGEL are also statistically significant at the 5% level with the expected signs, indicating that upgrades (downgrades) through the investment-speculative-grade boundary lead to significant decreases (increases) in abnormal CDS spreads.

We find that negative tone (NEG) surpassed downgrade in affecting the abnormal CDS spreads. Model 4 shows that the coefficient on NEG is positive at 0.1003 and is statistically significant at the 1% level. This indicates that the CDS spread reaction to negative tone is economically larger than the reaction to a downgrade: an increase in abnormal CDS spread by 2.56 bps for negative tone and 1.37 bps for a downgrade (i.e., $0.1003 \times 0.2553 \approx 2.56$ bps in Model 4 versus $0.0274 \times 0.5012 \approx 1.37$ bps in Model 3). Model 4 also shows that the inclusion of the tone variables increases the adjusted R-squared from 26% in Model 1 to 31%. This increase is higher than that from Model 1 to Model 2 when the variable DOWN is included (i.e., from 26% to 29%). Model 5 further includes the variable DOWN, and Model 6 further includes credit watch and rating outlooks. We continue to find that NEG is positively and significantly related to abnormal CDS spread change beyond credit rating changes and other rating actions at the 5% level in Models 5 and 6. The economic significance of a negative tone in Model 6 is more than twice that of a downgrade shown in Model 3, given a one-standard-deviation increase in the two variables (i.e., $0.1110 \times 0.2553 \approx 2.83$ bps in Model 6 versus $0.0274 \times 0.5012 \approx 1.37$ bps in Model 3).

The coefficients on the control variables LOCAL_MKT and VOLRISK_PREM are also significant and negative, consistent with Longstaff et al. (2011) who found that local stock returns and time-varying volatility risk premium are important in affecting CDS spreads.

We also find that the information value of a negative tone is significantly greater than that of a positive tone. This asymmetric information value of tone is also consistent with the literature that the market reaction to a downgrade is usually bigger than the reaction to an upgrade (e.g., Agarwal et al., 2016). Because a downgrade is a more severe event than an upgrade, CRAs usually provide more information to justify their downgrade reports (e.g., Beaver et al., 2006; and Jorion and Zhang, 2007). On the other hand, if CRAs include negative information in their upgrade reports, this would also attract more market attention than positive tone since it would be unexpected. Thus a negative tone in both upgrade and downgrade reports is more valuable than a positive tone, resulting in the observed asymmetric market reaction.

The tone variables in the rating reports also surpass the rating change itself in predicting future downgrades (i.e., the dummy variable, 1-YR FUTURE DOWNGRADE). Table 3 shows that a negative tone can significantly predict a future rating downgrade at the 10% level. Models 1 to 3 in Table 3 present the baseline results without the tone variables. Models 2 and 3 show that the downgrade dummy (DOWN) and the negative outlook (NEG_OUTLOOK) significantly predict future downgrades at the 1% level. The latter finding also corroborates the claim made by CRAs that rating outlooks are provided to indicate a likely future rating action (e.g., Moody's, 2013).

[Insert Table 3 about here]

Models 4 to 6 in Table 3 include the tone variables and reveal their superior ability to predict future rating changes. In Model 4, the coefficient on negative tone (NEG) is 0.7489 over a one-year time horizon and is statistically significant at the 1% level. This implies that a one-standard-deviation increase in NEG translates to an increase in the probability of a future downgrade of 19.1% over a one-year horizon (i.e., 0.7489×0.2553). Model 5 further includes the variable DOWN. The negative tone is still statistically significant at the 1% level, whereas DOWN is not statistically significant at the 10% level. The significant relation between tone and future downgrade indicates that the tone contains useful downgrade information. Even after we control for other rating actions in Model 6, the negative tone remains statistically significant at the 10% level. These results indicate that credit rating reports contain useful credit information beyond rating actions such as rating changes, watchlists, and outlooks in affecting CDS spreads and in predicting future downgrades.

As a robustness test, we use the lagged macroeconomic variables to decompose the tone information in the rating reports into "predicted" and "surprise" components. Table 4 reports the results from the prediction model.

[Insert Table 4 about here]

Table 4 shows that the conventional determinants of sovereign default risk can explain part of the tone but not the majority. In Models 1 and 2, we regress positive tone on the predictors and in Model 3 and 4, we regress negative tone on the predictors. Model 1 and Model 3 employ the sample of credit rating changes (with 166 reports); Models 2 and 4 employ the expanded sample of all types of rating actions such as watchlist and outlook (with 323 reports). All four models in Table 5 show that the coefficients of INITIAL_RATING, GDP_GROWTH, DEBT_GDP, FRES_GDP, TRADEBAL_GDP, and HIGH_STRESS are significantly related to positive and negative tone (mostly at the 1% or 5% level) with the expected signs. These results imply that higher initial ratings, higher GDP growth, a lower debt-to-GDP ratio, a higher ratio of foreign reserves to GDP, a higher ratio of trade balance to GDP, and a lower probability that the VIX index is in a high volatility state are significantly related to more positive tone and to less negative tone. However, we also observe that there is still a significant portion of the tone that cannot be explained by the macroeconomic variables (about 50% to 65%).

Next, we test whether the "predicted" and "surprise" tones affect abnormal CDS spreads and predict future downgrade differently. Table 5 reports the results. Models 1 and 2 employ CDS(-1,1) as the dependent variable; Models 3 and 4 employ the 1-YEAR FUTURE DOWNGRADE as the dependent variable.

[Insert Table 5 about here]

Table 5 shows that the negative "surprise" tone (NEG_S) is significantly related to the abnormal CDS spreads shown in Models 1 and 2. The coefficients on NEG_S are significantly positive at the 5% level. This finding indicates that the negative "surprise" tone is the main predictor of abnormal CDS spreads. In Models 3 and 4, we find that a negative predicted tone significantly predicts a future downgrade. The coefficient on the negative predicted tone (NEG_P) is statistically significant and positive at the 10% level in both models. Model 3 also shows that the coefficient on the negative surprise tone (NEG_S) is statistically significant and positive at the 5% level. But once we include the negative outlook (NEG_OUTLOOK) in Model 4, the coefficient on NEG_S becomes insignificant at the 10% level. It is not surprising that NEG_OUTLOOK strongly predicts a future downgrade since it is used to forecast intermediate rating actions in six months to two years. Hence our results here show that negative predicted tone is a strong predictor of a future downgrade and negative surprise tone is new to the sovereign CDS market.

Overall, we find that the sovereign credit rating reports contain valuable information for the sovereign CDS markets. The new information is different from rating actions and the conventional macroeconomic predictors of sovereign credit risk.

4.2 Dissecting Information Value of Sovereign Rating Reports

Given the finding that sovereign credit rating reports are useful and provide information value, we now attempt to determine the most important category of information content in credit rating reports.[17]

First, we regress CDS(-1,1) on the positive and negative tone within each content category (i.e., CONTENT_POS, CONTENT_NEG) that justify the rating actions in each report. In the same regression, we also include the residual portion of the positive and negative tone (POS_RES and NEG_RES) to assess the relative importance of the remaining information content in the same report. Models 1 to 5 in Table 6 report the five content categories: macroeconomic, public & external finance, debt dynamics, financial sector, and political & institutional.

[Insert Table 6 about here]

Table 6 shows that the CDS market places greater importance on the negative tone related to "debt dynamics" content in sovereign credit rating reports than it does on the other content categories. Specifically, we find that the coefficient on CONTENT_NEG is statistically significant and positive at the 5% level in Model 3, whereas it is not statistically significant in

[17] Note that we do not directly test the economic importance of the sixth category, "Others", which captures the remaining information content of the reports that is not in the five specific information categories identified.

the other four models at the 10% level (i.e., in Models 1, 2, 4, and 5). Moreover, we find that the coefficients on negative residual tones (NEG_RES) are also statistically significant and positive at the 5% level in the other four models (i.e., in Models 1, 2, 4, and 5). These results indicate that the negative tone related to "debt dynamics" is the most informative content for abnormal sovereign CDS spreads. Specifically, a one-standard-deviation increase in this specific tone results in a 1.97 bps increase in abnormal CDS spreads (i.e., 0.1873×0.1052). This accounts for approximately 70% of the total abnormal CDS market reaction to negative tone (which is about 2.83 bps in Model 6 in Table 2). This result also supports the sovereign rating approach used by Moody's (2013): "*Some indicators, however, particularly in the area of government and external debt, require estimation by Moody's analysts based on data provided by national statistical sources*" (page 4).

4.3 The Time-Varying Information Value of Sovereign Credit Rating Reports

In this section, we test whether there is a significant change in the quality of sovereign credit rating reports before and after the euro debt crisis. We introduce a dummy variable, POST2009, which equals 1 if the year of the current rating action is after 2009 (i.e., 2010 or later), and 0 otherwise. Table 7 reports the regression results.

[Insert Table 7 about here]

We find that the negative tone related to financial sector content in sovereign credit rating reports became less informative after the Eurozone debt crisis. Model 1 to 5 in Table 7 report the regression results on the four tone variables POS_RES, NEG_RES, CONTENT_POS and CONTENT_NEG (as defined in Table 4), downgrade dummy variable (DOWN), credit watch (NEG_WATCH), outlook (POS_OUTLOOK and NEG_OUTLOOK), POST2009, and its interactions with the tone variables, as well as other control variables. Model 4 shows that the coefficient on CONTENT_NEG (related to financial sector content) is significantly positive at the 1% level and the coefficient on the interaction term of POST2009 with CONTENT_NEG (POST2009×CONTENT_NEG) is significantly negative at the 5% level. This indicates a drop in the information value of negative tone related to financial sector content after 2009. Economically, prior to 2009, a one-standard-deviation increase in negative tone related to financial sector content results in an increase in sovereign CDS spreads of 4.37 bps (i.e., 0.6180×0.0707). This is reduced to −0.26 bps after 2009 (i.e., 0.0437 – 0.6547×0.0707), a decrease of more than 100 percent. This result indicates a loss of market confidence in Moody's assessment of financial sector-related risk in the rating reports after the 2009 euro debt crisis.

Overall, our results provide new evidence that Moody's possessed specific skill in analyzing the sovereign debt dynamics while assigning sovereign credit ratings. Moreover, we also find that Moody's sovereign risk assessment contains different types of information for the sovereign CDS markets and future rating actions. Last, we find that sovereign credit rating reports serve as a valuable source of information in understanding how CRAs' reputational capital in sovereign risk assessment varies over time.

5. ROBUSTNESS TESTS

In this section, we perform two sets of robustness tests. First, we investigate whether the CDS market reaction to tone has any drifts or reversals after the announcement. This test can further establish the usefulness of credit rating reports. Second, we expand our sample from rating reports to reports for all types of rating actions, including credit watch and rating outlook. watchlist and outlook actions may pre-empt rating changes or signal the direction of possible future rating changes (Bannier and Hirsch, 2010; Chung, Frost, and Kim, 2012; Alsakka and Gwilym, 2012). The reason for testing our findings in the expanded sample is that the literature usually focuses more on sovereign rating changes than on watchlist and outlook actions because sovereign ratings have a bigger economic impact on financial markets. As such, we expect our main results to be weaker in the expanded sample because CRAs' assessments of sovereign credit risk may be of higher quality for sovereign rating changes.

5.1. Post-Announcement Drift?

We investigate post-announcement long-run CDS market reaction to tone. We sort our sample of credit rating reports into quintiles based on positive and negative tone scores. We then construct five portfolios and test if the mean long-run abnormal CDS spread change of each portfolio is significantly different from zero across six post-announcement event windows: [1,10], [1,20], [1,30], [1,45], [1,60] and [1,90]. Owing to a relatively small number of observations in each portfolio, the result from a standard *t*-test may be biased. We therefore apply the bootstrap technique described by Efron and Tibshirani (1993) and Hull, Predescu, and White (2004). A detailed description of this technique is provided in Appendix C. Table 8 reports our results.

[Insert Table 8 about here]

Table 8, Panels A and B, reveal little evidence that post-announcement long-run CDS spreads are significantly related to tone. We find that only Portfolio 1, with the lowest positive tone, has systematic positive drift in the CDS after 20 days; the other drifts are mostly insignificant or inconsistent for different time periods. Hence we conclude that there are no systematic reversals after the rating announcements, indicating that sovereign credit rating reports do provide new information to the CDS markets.

5.2 Expanded Sample

We conduct the robustness tests using the expanded sample by including the watchlist and outlook rating reports. Descriptive statistics and correlation matrix of all the key variables and control variables for these 323 reports are reported in Table A3 and Table A4 of Appendix A. Table 9 presents the results.

[Insert Table 9 about here]

Models 1 to 4 in Table 9 show that negative tone still carries significant incremental credit information beyond rating actions. The coefficient on negative tone (NEG) is statistically significant and positive at the 1% level (in Model 1) and the 10% level (in Model 4). The weaker statistical significance in Model 4 shows that the tone information is less significant in those rating action reports related to watchlist and outlook only. A separate test on this reduced sample (323 – 166 = 157 reports) confirms this result.[18] Economically, a one-standard-deviation increase in NEG will lead to 1.4 bps increase in the abnormal CDS spread in Model 4 (i.e., 0.0571×0.2467), smaller than that in the 166 rating reports. These findings also suggest that the rating change reports contain the most valuable information.

Models 5 to 8 in Table 9 use the future downgrade as the dependent variable and show that the tone variables in all reports still provide valuable information about future rating actions. The coefficients on the negative tone (NEG) are statistically significant and positive at the 5% level across all four models. The economic significance of NEG in Model 8 is at 7.4% (i.e., 0.2986×0.2467 in Model 6), smaller than that in the sample of 166 rating reports.

Next, we investigate in the expanded sample whether the "predicted" or "surprise" tone variables can predict abnormal CDS movements and future downgrades. The results are reported in Table 10.

[Insert Table 10 about here]

Models 1 to 4 in Table 10 continue to show that the negative "surprise" tone carries significant incremental credit information beyond rating actions in sovereign CDS markets,

[18] This result is not reported here to save space but is available upon request.

similar to the main result in Table 5. The coefficient on negative "surprise" tone (NEG_S) is statistically significant and positive at the 5% level in Model 4. Models 5 to 8 show that the negative "predicted" tone (NEG_P) is a consistent predictor of future downgrades at the 5% level.

We also dissect the specific information contents in the expanded sample reports. Table 11 reports the findings.

[Insert Table 11 about here]

Similar to our main findings, Model 3 in Table 11 shows that the coefficient on CONTENT_NEG is statistically significant and positive for negative tone related to debt dynamics at the 10% level. The negative residual tone (NEG_RES) is statistically significant and positive in Models 2, 4, and 5 at the 10% level. These results are similar to the main result in Table 4 using 166 rating reports. In the expanded sample of rating action reports, we also find that negative tone in the macroeconomic content category is statistically significant at the 10% level. This result indicates that macroeconomic-related content matters more for the CDS market in the watchlist and outlook action reports.

Overall, we find consistent but slightly weaker empirical results in the expanded sample, indicating that less information value is contained in the reports for watchlist and outlook actions. Such a finding is not surprising since there are fewer direct economic consequences for rating actions that are not related to sovereign rating changes.

6. CONCLUSION

In this study, we dissect the information value of sovereign credit rating reports issued contemporaneously with the rating announcements by Moody's from 2003 to 2013. We find that Moody's sovereign rating reports contain valuable new information beyond credit rating actions, as well as conventional macroeconomic default predictors. The most valuable content in the reports comes from Moody's assessment of external debt dynamics. Interestingly, the information value of financial sector content declined after the Eurozone sovereign debt crisis in 2009, plausibly because investors lost confidence in CRAs' ability to assess financial risk. These results suggest that sovereign credit rating reports provide important information to investors who want to assess country-level credit risk in international capital markets.

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Table 1. Sample Selection, Summary Statistics and Correlation Matrix

This table presents the sample selection procedure (Panel A), the summary statistics of key variables (Panel B), and the correlation matrix of variables (Panel C) for the data corresponding to Moody's credit rating changes, watchlist, and outlook actions. For definitions of key variables, please refer to Table A1. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Sample Selection

Source / adjustment	**Sample size (observations removed)**					
	Credit rating changes		**Watchlists**		**Outlooks**	
Observations under investigation	197		83		125	
Adjusting for CDS data availability	166	(31)	68	(15)	89	(36)
Final sample sizes	166		68		89	

Final sample sizes and breakdown	
Credit rating changes	
Upgrades	80
Investment grade	38
Speculative grade	42
Downgrades	86
Investment grade	56
Speculative grade	30
Credit rating changes	***166***
Watchlists	
Positive watch	38
Negative watch	30
Credit rating changes and watchlists	***234***
Outlooks	
Positive outlook	51
Negative outlook	38
Credit rating changes, watchlists and outlooks	***323***

Panel B: Summary Statistics

	N	Mean	Median	Std Dev	Min	Max
Key Dependent Variables						
CDS(-1,1)	166	0.0055	0.0012	0.0716	-0.2044	0.2720
1-YR FUTURE DOWNGRADE	166	0.2108	0.0000	0.4091	0.0000	1.0000
Key Independent Variables						
POS	166	0.3621	0.3529	0.1992	0.0000	0.8571
NEG	166	0.3984	0.4000	0.2553	0.0000	0.9375
DOWN	166	0.5181	1.0000	0.5012	0.0000	1.0000
NEG_WATCH	166	0.0663	0.0000	0.2495	0.0000	1.0000
POS_OUTLOOK	166	0.1145	0.0000	0.3193	0.0000	1.0000
NEG_OUTLOOK	166	0.3855	0.0000	0.4882	0.0000	1.0000
INITIAL_STATUS	166	0.4337	0.0000	0.4971	0.0000	1.0000
RISING_STAR	166	0.0663	0.0000	0.2495	0.0000	1.0000
FALLEN_ANGEL	166	0.0482	0.0000	0.2148	0.0000	1.0000
LOCAL_MKT	166	0.0005	-0.0010	0.0317	-0.1014	0.1808
FX_RATE	166	0.0026	0.0000	0.0192	-0.0209	0.2200
US_MKT	166	0.0004	0.0008	0.0222	-0.1367	0.0644
TREASURY_MKT	166	0.0000	-0.0001	0.0008	-0.0021	0.0034
VOLRISK_PREM	166	-0.0040	-0.0016	0.0417	-0.2043	0.0957
ADS_INDEX	166	0.0005	0.0010	0.0428	-0.1189	0.1671
INITIAL_RATING	166	13.6687	13.0000	4.4222	2.0000	22.0000
RECENT_DEFAULT	166	0.0723	0.0000	0.2597	0.0000	1.0000
GDP_GROWTH	166	0.0000	0.0000	0.0007	-0.0075	0.0030
DEBT_GDP	166	0.6355	0.5325	0.4097	0.0506	2.0300
FRES_GDP	166	0.1174	0.0751	0.1284	0.0047	0.8869
FRES_GROWTH	166	0.1764	0.0848	0.4646	-0.4592	3.5224
FX_GROWTH	166	0.0012	0.0000	0.0786	-0.1677	0.3841
TRADEBAL_GDP	166	-0.0422	-0.0480	0.1380	-0.3683	0.4183
SP500	166	0.0035	0.0084	0.0472	-0.1694	0.1077
FISCAL_FREEDOM	166	75.3669	74.7000	10.7617	42.2000	99.9000
MONETARY_FREEDOM	166	76.6964	77.6000	7.4211	46.1000	94.3000
FINANCIAL_FREEDOM	166	58.1325	60.0000	15.9775	20.0000	90.0000
HIGH_STRESS	166	0.1282	0.0013	0.3035	0.0000	1.0000
POST2009	166	0.5542	1.0000	0.4986	0.0000	1.0000
Other Tone Variables						
MACRO_POS	166	0.1571	0.1250	0.1168	0.0000	0.5000
MACRO_NEG	166	0.1370	0.1111	0.1192	0.0000	0.4231
PEF_POS	166	0.0735	0.0580	0.0715	0.0000	0.3333
PEF_NEG	166	0.0503	0.0404	0.0545	0.0000	0.2727
DEBT_POS	166	0.0715	0.0597	0.0708	0.0000	0.4000
DEBT_NEG	166	0.0879	0.0548	0.1052	0.0000	0.6111
FIN_POS	166	0.0142	0.0000	0.0292	0.0000	0.1539
FIN_NEG	166	0.0442	0.0000	0.0707	0.0000	0.3214
POL_POS	166	0.0150	0.0000	0.0284	0.0000	0.1333
POL_NEG	166	0.0377	0.0000	0.0561	0.0000	0.3529

Panel C: Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	POS	-													
		-													
(2)	NEG	-0.86***	-												
		(0.00)	-												
(3)	DOWN	-0.86***	0.87***	-											
		(0.00)	*(0.00)*	-											
(4)	NEG_WATCH	-0.30***	0.23**	0.26***	-										
		(0.00)	*(0.00)*	*(0.00)*	-										
(5)	POS_OUTLOOK	0.32***	-0.37***	-0.37***	-0.10	-									
		(0.00)	*(0.00)*	*(0.00)*	*(0.22)*	-									
(6)	NEG_OUTLOOK	-0.70***	0.74***	0.76***	0.34***	-0.28***	-								
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	-								
(7)	INITIAL_STATUS	0.19*	-0.09	-0.18*	0.01	-0.05	-0.19*	-							
		(0.02)	*(0.26)*	*(0.02)*	*(0.89)*	*(0.54)*	*(0.01)*	-							
(8)	RISING_STAR	0.33***	-0.24**	-0.28***	-0.07	0.13	-0.21**	0.30***	-						
		(0.00)	*(0.00)*	*(0.00)*	*(0.36)*	*(0.09)*	*(0.01)*	*(0.00)*	-						
(9)	FALLEN_ANGEL	-0.21**	0.26***	0.22**	-0.06	-0.08	0.17*	-0.20*	-0.06	-					
		(0.01)	*(0.00)*	*(0.00)*	*(0.44)*	*(0.30)*	*(0.03)*	*(0.01)*	*(0.44)*	-					
(10)	LOCAL_MKT	0.03	-0.07	-0.03	-0.03	0.06	0.04	-0.03	0.05	-0.04	-				
		(0.70)	*(0.39)*	*(0.69)*	*(0.68)*	*(0.44)*	*(0.59)*	*(0.66)*	*(0.53)*	*(0.63)*	-				
(11)	FX_RATE	-0.02	-0.05	0.01	0.00	0.00	0.05	-0.03	0.03	-0.05	0.63***	-			
		(0.83)	*(0.52)*	*(0.91)*	*(0.99)*	*(0.96)*	*(0.52)*	*(0.72)*	*(0.73)*	*(0.51)*	*(0.00)*	-			
(12)	US_MKT	0.06	-0.01	-0.08	0.00	0.01	-0.07	0.08	0.04	-0.01	0.28***	0.15	-		
		(0.42)	*(0.85)*	*(0.31)*	*(1.00)*	*(0.94)*	*(0.38)*	*(0.30)*	*(0.60)*	*(0.94)*	*(0.00)*	*(0.06)*	-		
(13)	TREASURY_MKT	-0.06	0.09	0.10	0.23**	0.01	0.05	0.06	0.08	-0.00	0.13	0.06	0.20*	-	
		(0.47)	*(0.28)*	*(0.20)*	*(0.00)*	*(0.89)*	*(0.53)*	*(0.42)*	*(0.32)*	*(0.99)*	*(0.09)*	*(0.42)*	*(0.01)*	-	
(14)	VOLRISK_PREM	0.07	-0.08	-0.09	-0.05	0.04	-0.12	0.05	0.09	-0.01	-0.20*	-0.16*	-0.08	-0.06	-
		(0.36)	*(0.32)*	*(0.26)*	*(0.52)*	*(0.59)*	*(0.14)*	*(0.51)*	*(0.25)*	*(0.87)*	*(0.01)*	*(0.04)*	*(0.33)*	*(0.42)*	-
(15)	ADS_INDEX	*0.05*	*-0.09*	*-0.06*	*0.05*	*0.03*	*-0.09*	*-0.04*	*-0.06*	*0.07*	*-0.04*	*-0.07*	*-0.05*	*-0.00*	-0.05
		(0.53)	*(0.25)*	*(0.47)*	*(0.49)*	*(0.70)*	*(0.27)*	*(0.65)*	*(0.45)*	*(0.40)*	*(0.62)*	*(0.36)*	*(0.52)*	*(0.98)*	*(0.54)*

Table 2. The Information Value of Credit Rating Reports

This table presents the information value of the tone in credit rating reports during credit rating changes announced by Moody's from 2003 to 2013. The dependent variable is the 3-day cumulative abnormal CDS spread percentage change CDS(-1,1), calculated as the CDS spread percentage change of the sovereign country in excess of the market CDS spread percentage change. For definitions of key variables, please refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: CDS(-1,1)					
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
POS				0.0521	0.0520	0.0615
				(1.09)	(1.12)	(1.29)
NEG				0.1003***	0.1005**	0.1110**
				(2.87)	(2.25)	(2.27)
DOWN		0.0270***	0.0274*		-0.0001	0.0058
		(2.70)	(1.92)		(-0.01)	(0.28)
NEG_WATCH			0.0074			0.0140
			(0.28)			(0.54)
POS_OUTLOOK			0.0126			0.0155
			(0.84)			(1.00)
NEG_OUTLOOK			0.0023			-0.0074
			(0.15)			(-0.46)
INITIAL_STATUS	-0.0113	-0.0095	-0.0084	-0.0138	-0.0138	-0.0135
	(-1.11)	(-0.93)	(-0.76)	(-1.38)	(-1.29)	(-1.17)
RISING_STAR	-0.0514***	-0.0378**	-0.0387**	-0.0396**	-0.0396**	-0.0408**
	(-3.12)	(-2.31)	(-2.31)	(-2.35)	(-2.35)	(-2.35)
FALLEN_ANGEL	0.1068***	0.0946***	0.0960***	0.0855**	0.0855**	0.0870**
	(3.16)	(2.80)	(2.81)	(2.50)	(2.49)	(2.53)
LOCAL_MKT	-0.4439*	-0.4232*	-0.4304*	-0.4098*	-0.4097*	-0.4043*
	(-1.90)	(-1.80)	(-1.85)	(-1.83)	(-1.83)	(-1.83)
FX_RATE	-0.0695	-0.0985	-0.0931	-0.0186	-0.0185	-0.0054
	(-0.32)	(-0.47)	(-0.45)	(-0.08)	(-0.08)	(-0.02)
US_MKT	-0.2900	-0.2333	-0.2247	-0.2992	-0.2994	-0.2998
	(-1.11)	(-0.87)	(-0.81)	(-1.14)	(-1.13)	(-1.10)
TREASURY_MKT	1.3398	-0.9805	-1.6765	-0.8508	-0.8474	-2.2208
	(0.20)	(-0.15)	(-0.25)	(-0.14)	(-0.14)	(-0.33)
VOLRISK_PREM	-0.3011**	-0.2800**	-0.2798**	-0.2692**	-0.2692**	-0.2719**
	(-2.36)	(-2.27)	(-2.22)	(-2.15)	(-2.15)	(-2.09)
ADS_INDEX	-0.0167	0.0129	0.0101	0.0389	0.0389	0.0306
	(-0.12)	(0.09)	(0.07)	(0.27)	(0.27)	(0.22)
INTERCEPT	0.0080	-0.0070	-0.0105	-0.0496	-0.0495	-0.0602*
	(1.09)	(-0.68)	(-0.85)	(-1.58)	(-1.59)	(-1.80)
N	166	166	166	166	166	166
Adj. R^2	0.26	0.29	0.29	0.31	0.31	0.32

Table 3. The Prediction of Credit Rating Reports for Future Downgrade

This table presents the predictive power of Moody's credit rating reports for future rating changes for the period 2003–2013. The dependent variable is the dummy variable, 1-YEAR FUTURE DOWNGRADE, which equals 1 if there is a downgrade in the next one-year horizon after the current rating action. For definitions of key variables, refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	Dependent Variable: 1-Year Future Rating Downgrade					
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
POS				-0.0772	0.0041	0.0680
				(-0.40)	(0.02)	(0.35)
NEG				0.7489***	0.6547***	0.4374*
				(4.57)	(2.85)	(1.94)
DOWN		0.3750***	0.0708		0.0874	-0.0672
		(6.54)	(0.98)		(0.72)	(-0.68)
NEG_WATCH			0.0986			0.1131
			(0.58)			(0.71)
POS_OUTLOOK			-0.0182			-0.0075
			(-0.82)			(-0.29)
NEG_OUTLOOK			0.3898***			0.3466***
			(4.08)			(3.39)
INITIAL_STATUS	-0.1301*	-0.1055*	-0.0862	-0.1379**	-0.1329**	-0.1064*
	(-1.91)	(-1.75)	(-1.51)	(-2.30)	(-2.23)	(-1.85)
RISING_STAR	-0.1506**	0.0382	0.0290	0.0499	0.0515	0.0339
	(-2.49)	(0.84)	(0.70)	(1.06)	(1.12)	(0.84)
FALLEN_ANGEL	-0.0091	-0.1792	-0.1649	-0.2498	-0.2467	-0.2063
	(-0.06)	(-1.12)	(-1.07)	(-1.65)	(-1.60)	(-1.35)
LOCAL_MKT	-1.7795	-1.4927	-1.8174	-1.3724	-1.3802	-1.7029
	(-0.97)	(-0.99)	(-1.29)	(-1.04)	(-1.02)	(-1.30)
FX_RATE	2.7541	2.3516	2.3439	2.8612*	2.7958*	2.6526*
	(1.40)	(1.50)	(1.55)	(1.96)	(1.89)	(1.81)
US_MKT	-2.2241*	-1.4372	-1.2558	-2.0197*	-1.9039*	-1.5744
	(-1.93)	(-1.33)	(-1.18)	(-1.90)	(-1.76)	(-1.46)
TREASURY_MKT	95.1642***	62.9879*	64.3118**	67.9878**	65.5668**	63.7407**
	(2.67)	(1.90)	(2.17)	(2.15)	(2.04)	(2.18)
VOLRISK_PREM	-1.6596**	-1.3668*	-1.1619*	-1.3240*	-1.3128*	-1.1433
	(-1.98)	(-1.96)	(-1.68)	(-1.78)	(-1.80)	(-1.61)
ADS_INDEX	-1.6515***	-1.2410**	-1.0828**	-1.0535*	-1.0611*	-0.9938*
	(-2.61)	(-2.16)	(-2.02)	(-1.74)	(-1.78)	(-1.80)
INTERCEPT	0.2663***	0.0587**	0.0539*	-0.0019	-0.0413	-0.0493
	(5.75)	(1.99)	(1.68)	(-0.02)	(-0.34)	(-0.46)
N	166	166	166	166	166	166
Adj. R^2	0.15	0.33	0.43	0.36	0.37	0.44

Table 4. Prediction Model for the Information Value of Credit Rating Reports

This table presents how much content in the rating reports can be explained by lagged fundamental country-level default risk factors for the period 2003–2013. The dependent variable is positive tone (POS) in Models 1 and 2, and negative tone (NEG) in Models 3 and 4. Model 1 and Model 3 employ a sample of 166 credit rating reports. Models 2 and 4 employ the full sample of 323 credit action reports. For definitions of key variables, refer to Table A1. The t-statistics are calculated based on robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	Positive Tone		Negative Tone	
Independent Variables	Model 1	Model 2	Model 3	Model 4
INITIAL_STATUS	0.0759	0.0625*	-0.0649	-0.0508
	(1.57)	(1.66)	(-1.14)	(-1.30)
INITIAL_RATING	-0.0119**	-0.0086*	0.0158**	0.0113**
	(-2.03)	(-1.87)	(2.03)	(2.15)
RECENT_DEFAULT	-0.1301**	-0.1217**	0.0773	0.0765
	(-2.43)	(-2.46)	(1.24)	(1.35)
GDP_GROWTH	0.7487**	0.7898***	-1.4403***	-1.2859***
	(2.25)	(2.78)	(-3.43)	(-3.93)
DEBT_GDP	-0.1713***	-0.1401***	0.1987***	0.2163***
	(-4.02)	(-4.53)	(3.60)	(6.10)
FRES_GDP	0.4504***	0.3207***	-0.8509***	-0.6977***
	(5.07)	(4.76)	(-6.38)	(-7.69)
FRES_GROWTH	0.0305	0.0254	-0.0792***	-0.0532***
	(1.46)	(1.40)	(-2.95)	(-2.73)
FX_GROWTH	0.0098	-0.2676**	-0.0672	0.1094
	(0.06)	(-2.01)	(-0.34)	(0.72)
TRADEBAL_GDP	0.2728***	0.2109***	-0.3501***	-0.2217**
	(3.05)	(2.85)	(-2.83)	(-2.47)
SP500	-0.4062	-0.2808	0.3402	0.2821
	(-1.22)	(-1.24)	(0.92)	(1.12)
FISCAL_FREEDOM	-0.0022*	-0.0023*	0.0029*	0.0021
	(-1.66)	(-1.90)	(1.69)	(1.61)
MONETARY_FREEDOM	0.0022	0.0024	-0.0036	-0.0052***
	(1.10)	(1.39)	(-1.35)	(-2.68)
FINANCIAL_FREEDOM	-0.0010	-0.0017**	-0.0001	0.0011
	(-1.03)	(-2.21)	(-0.06)	(1.18)
HIGH_STRESS	-0.0904*	-0.0999***	0.0984*	0.1275***
	(-1.95)	(-2.68)	(1.87)	(3.31)
INTERCEPT	0.6057***	0.5930***	0.2748	0.3898*
	(3.08)	(3.29)	(0.96)	(1.96)
N	166	323	166	323
Adj. R^2	0.46	0.35	0.50	0.45

Table 5. The Information Value of "Predicted" and "Surprise" Components

This table presents the information value of "predicted" and "surprise" components. POS_P and NEG_P are the positive and negative predicted tone from Table 5, while POS_S and NEG_S are the positive and negative surprise tone. The dependent variable is 3-day cumulative abnormal CDS(-1,1) in Models 1 and 2. The dependent variable is the dummy variable, 1-YEAR FUTURE DOWNGRAE in Models 3 and 4. For definitions of key variables, refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	CDS(-1,1)		1-yer Future Downgrade	
Independent Variables	Model 1	Model 2	Model 3	Model 4
POS_P	-0.1057	-0.0853	0.5315	0.1429
	(-1.03)	(-0.78)	(0.85)	(0.24)
NEG_P	0.0051	0.0287	1.3186***	0.8482*
	(0.06)	(0.31)	(2.86)	(1.86)
POS_S	0.0563	0.0674	-0.0529	0.0854
	(1.17)	(1.40)	(-0.23)	(0.43)
NEG_S	0.1103**	0.1201**	0.5146**	0.3440
	(2.49)	(2.51)	(2.06)	(1.47)
DOWN	-0.0023	0.0029	0.0309	-0.1283
	(-0.11)	(0.13)	(0.24)	(-1.24)
NEG_WATCH		0.0195		0.1265
		(0.72)		(0.82)
POS_OUTLOOK		0.0139		0.0252
		(0.83)		(0.85)
NEG_OUTLOOK		-0.0093		0.3481***
		(-0.52)		(3.43)
INITIAL_STATUS	-0.0063	-0.0068	-0.1567**	-0.1082
	(-0.54)	(-0.56)	(-2.38)	(-1.64)
RISING_STAR	0.0028	0.0018	0.0539	0.0310
	(0.18)	(0.11)	(1.19)	(0.73)
FALLEN_ANGEL	0.0230	0.0255	-0.2238	-0.1787
	(0.82)	(0.93)	(-1.45)	(-1.15)
LOCAL_MKT	-0.4382*	-0.4241*	-1.2565	-1.5079
	(-1.76)	(-1.74)	(-0.93)	(-1.17)
FX_RATE	-0.0389	-0.0261	2.8587*	2.7224*
	(-0.15)	(-0.10)	(1.89)	(1.85)
US_MKT	-0.5049*	-0.5118*	-2.1158*	-1.8360*
	(-1.89)	(-1.87)	(-1.89)	(-1.67)
TREASURY_MKT	0.9582	-0.8425	61.3743*	60.1890**
	(0.15)	(-0.12)	(1.91)	(2.04)
VOLRISK_PREM	-0.3045**	-0.3055**	-1.2395*	-0.9986
	(-2.34)	(-2.26)	(-1.67)	(-1.40)
ADS_INDEX	-0.0217	-0.0316	-0.9954	-0.9587
	(-0.14)	(-0.20)	(-1.58)	(-1.61)
INTERCEPT	0.0412	0.0227	-0.4466	-0.2060
	(0.67)	(0.33)	(-1.21)	(-0.58)
N	166	166	166	166
Adj. R^2	0.23	0.24	0.38	0.46

Table 6. Dissecting Information Value of Credit Rating Reports

This table presents the economic importance of specific content categories in credit rating reports during credit rating changes announced by Moody's in the period 2003–2013. Models 1 to 5 present the results for five content categories. The positive and negative tone related to each of these specific content categories are represented by CONTENT_POS and CONTENT_NEG. POS_RES and NEG_RES are the residual positive and negative tone related to other content. The dependent variable is 3-day cumulative abnormal CDS(-1,1). For definitions of key variables, refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Macroeconomic	(2) Public & External Finance	(3) Debt Dynamics	(4) Financial Sector	(5) Political & Institutional
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
POS_RES	0.1007*	0.0643	0.0528	0.0562	0.0568
	(1.71)	(1.25)	(1.17)	(1.17)	(1.18)
NEG_RES	0.1220**	0.1131**	0.0835*	0.1139**	0.1126**
	(2.16)	(2.26)	(1.73)	(2.04)	(2.36)
CONTENT_POS	0.0193	0.0522	0.1433*	0.2678	0.0691
	(0.36)	(0.72)	(1.90)	(1.44)	(0.41)
CONTENT_NEG	0.0948	0.0552	0.1873**	0.0961	-0.0667
	(1.49)	(0.58)	(2.57)	(1.21)	(-0.63)
DOWN	0.0078	0.0075	0.0075	0.0063	0.0041
	(0.37)	(0.35)	(0.36)	(0.29)	(0.20)
NEG_WATCH	0.0121	0.0134	0.0136	0.0163	0.0211
	(0.43)	(0.51)	(0.53)	(0.59)	(0.79)
POS_OUTLOOK	0.0241	0.0147	0.0164	0.0194	0.0133
	(1.52)	(0.95)	(1.06)	(1.27)	(0.81)
NEG_OUTLOOK	-0.0062	-0.0085	-0.0056	-0.0075	-0.0036
	(-0.38)	(-0.51)	(-0.36)	(-0.46)	(-0.22)
INITIAL_STATUS	-0.0172	-0.0129	-0.0207*	-0.0143	-0.0085
	(-1.37)	(-1.10)	(-1.70)	(-1.17)	(-0.78)
RISING_STAR	-0.0382**	-0.0411**	-0.0386**	-0.0397**	-0.0433**
	(-2.25)	(-2.33)	(-2.25)	(-2.23)	(-2.44)
FALLEN_ANGEL	0.0862**	0.0857**	0.0755**	0.0882**	0.0809**
	(2.46)	(2.48)	(2.13)	(2.56)	(2.29)
LOCAL_MKT	-0.3696	-0.4083*	-0.3013	-0.4158*	-0.3911*
	(-1.59)	(-1.83)	(-1.39)	(-1.80)	(-1.79)
FX_RATE	-0.0760	-0.0079	-0.1546	0.0042	-0.0631
	(-0.31)	(-0.03)	(-0.71)	(0.02)	(-0.27)
US_MKT	-0.3177	-0.2832	-0.2827	-0.2852	-0.2545
	(-1.13)	(-1.02)	(-1.03)	(-1.11)	(-0.97)
TREASURY_MKT	-3.2455	-2.0480	-3.1403	-2.8108	-2.6997
	(-0.47)	(-0.31)	(-0.46)	(-0.41)	(-0.41)
VOLRISK_PREM	-0.2653**	-0.2748**	-0.2565*	-0.2687**	-0.2767**
	(-2.00)	(-2.10)	(-1.89)	(-2.02)	(-2.16)
ADS_INDEX	0.0281	0.0424	0.0496	0.0162	0.0276
	(0.20)	(0.29)	(0.34)	(0.11)	(0.20)
INTERCEPT	-0.0630*	-0.0588*	-0.0595*	-0.0623*	-0.0550
	(-1.90)	(-1.75)	(-1.83)	(-1.84)	(-1.65)
N	166	166	166	166	166
Adj. R^2	0.32	0.32	0.33	0.32	0.33

Table 7. A Natural Experiment: The 2009 Eurozone Debt Crisis

This table presents the time-varying nature of the information quality provided by Moody's before and after the 2009 Eurozone sovereign debt crisis. Models 1 to 5 present the results for five content categories. The positive and negative tone related to each of these specific content categories are represented by CONTENT_POS and CONTENT_NEG in each of the five models. POS_RES and NEG_RES are the residual positive and negative tone related to other content. POST2009 is a dummy variable that equals 1 if the year of the current rating action is after 2009, and 0 otherwise. The dependent variable is 3-day cumulative abnormal CDS(-1,1). For definitions of key variables, please refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

	(1) Macroeconomic	(2) Public & External Finance	(3) Debt Dynamics	(4) Financial Sector	(5) Political & Institutional
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
POS_RES	0.1018	0.0725	0.0551	0.0554	0.0468
	(1.25)	(0.96)	(0.79)	(0.81)	(0.65)
NEG_RES	0.1715**	0.1377*	0.1182	0.1160*	0.1573**
	(2.24)	(1.87)	(1.54)	(1.75)	(2.32)
CONTENT_POS	0.0359	0.0012	0.1296	0.1495	0.3403
	(0.48)	(0.01)	(1.35)	(0.50)	(1.50)
CONTENT_NEG	0.1066	0.1214	0.2105*	0.6180***	-0.0969
	(0.99)	(0.98)	(1.66)	(2.65)	(-0.59)
POST2009	0.1208	0.1019	0.0895	0.0701	0.0689
	(1.51)	(1.30)	(1.19)	(0.97)	(0.99)
POST2009xPOS_RES	-0.0809	-0.1282	-0.1020	-0.0639	-0.0340
	(-0.68)	(-1.04)	(-0.88)	(-0.60)	(-0.33)
POST2009xNEG_RES	-0.1643	-0.1199	-0.1132	-0.0282	-0.1114
	(-1.52)	(-1.30)	(-1.18)	(-0.34)	(-1.28)
POST2009xCONTENT_POS	-0.1861	0.0409	-0.0138	-0.1777	-0.8260**
	(-1.37)	(0.27)	(-0.10)	(-0.50)	(-2.52)
POST2009xCONTENT_NEG	-0.1118	-0.2356	-0.1212	-0.6547**	0.0629
	(-0.87)	(-1.29)	(-0.78)	(-2.59)	(0.32)
DOWN	-0.0031	-0.0028	-0.0013	-0.0144	-0.0008
	(-0.15)	(-0.13)	(-0.06)	(-0.64)	(-0.04)
NEG_WATCH	0.0048	0.0090	0.0083	0.0103	0.0232
	(0.17)	(0.34)	(0.31)	(0.37)	(0.80)
POS_OUTLOOK	0.0234	0.0097	0.0164	0.0208	0.0095
	(1.37)	(0.59)	(1.00)	(1.27)	(0.57)
NEG_OUTLOOK	-0.0048	-0.0062	-0.0054	-0.0082	-0.0070
	(-0.28)	(-0.36)	(-0.33)	(-0.49)	(-0.41)
INITIAL_STATUS	-0.0225*	-0.0169	-0.0238*	-0.0152	-0.0137
	(-1.73)	(-1.40)	(-1.90)	(-1.28)	(-1.21)
RISING_STAR	-0.0409**	-0.0488***	-0.0408**	-0.0448**	-0.0433***
	(-2.39)	(-2.80)	(-2.35)	(-2.30)	(-2.63)
FALLEN_ANGEL	0.0877**	0.0864**	0.0768**	0.0904***	0.0827**
	(2.43)	(2.40)	(2.08)	(2.88)	(2.17)
LOCAL_MKT	-0.3933	-0.4466*	-0.3377	-0.4163*	-0.4377*
	(-1.65)	(-1.95)	(-1.47)	(-1.82)	(-1.91)
FX_RATE	-0.0172	0.0485	-0.0768	-0.1678	0.0009
	(-0.07)	(0.20)	(-0.33)	(-0.68)	(0.00)
US_MKT	-0.3860	-0.3184	-0.3377	-0.0648	-0.2559
	(-1.29)	(-1.09)	(-1.18)	(-0.24)	(-0.93)
TREASURY_MKT	-3.0015	-1.9976	-2.8171	-4.9323	-3.8634
	(-0.41)	(-0.28)	(-0.39)	(-0.70)	(-0.54)
VOLRISK_PREM	-0.2843**	-0.2932**	-0.2597*	-0.2563*	-0.2923**
	(-2.01)	(-2.13)	(-1.80)	(-1.97)	(-2.17)
ADS_INDEX	0.0037	0.0266	0.0332	0.0270	0.0114
	(0.03)	(0.18)	(0.22)	(0.20)	(0.08)
INTERCEPT	-0.0761*	-0.0649	-0.0685*	-0.0714*	-0.0640
	(-1.81)	(-1.56)	(-1.66)	(-1.73)	(-1.57)
N	166	166	166	166	166
Adj. R^2	0.34	0.34	0.35	0.38	0.36

Table 8. Post-Announcement CDS Drift

This table presents the information value of tone in Moody's credit rating reports in predicting future abnormal sovereign CDS spreads for the period 2003–2013. Panel A and Panel B show the results of similar portfolios based on positive (POS) and negative (NEG) tone quintiles. The variables of interest in all portfolios are CDS(1,10), CDS(1,20), CDS(1,30), CDS(1,45), CDS(1,60) and CDS(1,90), which are the mean abnormal CDS spread percentage changes over the event windows [1,10], [1,20], [1,30], [1,45], [1,60] and [1,90] respectively. For definitions of key variables, refer to Table A1. We apply the bootstrap technique described by Efron and Tibshirani (1993) and Hull, Predescu, and White (2004) given the small sample size. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Portfolios based on Positive Tone Score (POS)

Portfolio	N	Mean tone	Mean CDS Spread Percent Changes (%)					
			CDS(1,10)	CDS(1,20)	CDS(1,30)	CDS(1,45)	CDS(1,60)	CDS(1,90)
1	33	0.118	-0.02	1.31	6.10**	10.57**	9.75**	19.37**
			(-0.01)	(0.78)	(1.88)	(1.94)	(1.77)	(2.00)
2	33	0.202	-1.38	-0.11	5.22	3.69	-2.68	1.99
			(-0.46)	(-0.04)	(1.35)	(0.74)	(-0.35)	(0.17)
3	34	0.340	0.12	-2.95	-0.78	0.34	-1.49	-1.14
			(0.09)	(-1.16)	(-0.19)	(0.08)	(-0.30)	(-0.13)
4	33	0.498	-3.55	-0.80	-0.34	-1.16	-0.97	9.32
			(-1.27)	(-0.26)	(-0.11)	(-0.21)	(-0.16)	(1.14)
5	33	0.639	-0.23	0.72	1.30	0.53	1.47	4.90
			(-0.16)	(0.39)	(0.69)	(0.21)	(0.39)	(1.60)

Panel B: Portfolios based on Negative Tone Score (NEG)

Portfolio	N	Mean tone	Mean CDS Spread Percent Changes (%)					
			CDS(1,10)	CDS(1,20)	CDS(1,30)	CDS(1,45)	CDS(1,60)	CDS(1,90)
1	33	0.753	0.94	2.55	5.80	4.86	5.81	18.32*
			(0.44)	(0.96)	(1.46)	(0.80)	(0.84)	(1.70)
2	33	0.583	-1.34	-2.44	5.18**	8.20**	-0.08	-1.79
			(-0.87)	(-1.29)	(2.05)	(1.97)	(-0.01)	(-0.16)
3	34	0.394	1.06	3.40	6.02	7.24*	6.44	13.98**
			(0.44)	(1.34)	(1.65)	(2.05)	(1.40)	(1.97)
4	33	0.198	-2.01	0.46	-0.62	2.52	1.04	8.37
			(-1.15)	(0.22)	(-0.32)	(0.56)	(0.21)	(1.03)
5	33	0.071	-3.72	-5.80**	-4.89	-8.85**	-6.82	-4.11
			(-1.37)	(-1.86)	(-1.31)	(-2.12)	(-1.36)	(-0.83)

Table 9. Robustness Test 1

This table presents the usefulness of credit action reports (including rating changes, watchlists, and outlooks) released by Moody's from 2003 to 2013. The dependent variable is the 3-day cumulative abnormal CDS(-1,1) from Models 1 to 4 and the dummy variable 1-YEAR FUTURE DOWNGRADE from Models 5 to 8. For definitions of key variables, refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	CDS(-1,1)				1-year Future Downgrade			
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
POS	0.0005	0.0036	0.0054	0.0042	-0.3670***	-0.3717***	-0.0254	-0.0027
	(0.01)	(0.10)	(0.15)	(0.11)	(-2.94)	(-2.93)	(-0.27)	(-0.03)
NEG	0.0553**	0.0554*	0.0594**	0.0571*	0.6832***	0.7366***	0.3176**	0.2986**
	(2.03)	(1.91)	(1.99)	(1.80)	(6.24)	(5.96)	(2.57)	(2.08)
UP		-0.0149		-0.0098		-0.0580**		0.0530
		(-1.61)		(-0.80)		(-2.40)		(1.33)
DOWN		-0.0088		-0.0062		-0.0963		0.0696
		(-0.85)		(-0.48)		(-1.27)		(0.86)
POS_WATCH			0.0022	-0.0005			0.0105	0.0258
			(0.18)	(-0.04)			(0.62)	(1.17)
NEG_WATCH			0.0057	0.0037			0.4660***	0.4879***
			(0.48)	(0.26)			(6.00)	(5.56)
POS_OUTLOOK			0.0136	0.0075			0.0112	0.0490
			(1.41)	(0.62)			(0.65)	(1.29)
NEG_OUTLOOK			0.0088	0.0043			0.2432***	0.2710***
			(0.64)	(0.30)			(3.37)	(3.53)
INITIAL_STATUS	-0.0032	-0.0032	-0.0027	-0.0029	-0.0632	-0.0624	-0.0358	-0.0349
	(-0.42)	(-0.42)	(-0.34)	(-0.36)	(-1.52)	(-1.52)	(-0.99)	(-0.95)
RISING_STAR	-0.0091	-0.0006	-0.0040	-0.0011	0.0372	0.0664*	0.0234	0.0111
	(-0.64)	(-0.04)	(-0.27)	(-0.07)	(1.08)	(1.79)	(0.94)	(0.44)
FALLEN_ANGEL	0.0243	0.0281	0.0269	0.0286	-0.3061**	-0.2653*	-0.1134	-0.1336
	(0.92)	(1.05)	(0.99)	(1.06)	(-2.14)	(-1.81)	(-0.78)	(-0.89)
LOCAL_MKT	-0.5212***	-0.5302***	-0.5409***	-0.5374***	-1.4491	-1.4913*	-1.1341	-1.1507
	(-2.91)	(-2.97)	(-3.00)	(-2.97)	(-1.61)	(-1.65)	(-1.43)	(-1.45)
FX_RATE	-0.1913	-0.1598	-0.1565	-0.1522	2.4340	2.6915*	2.1541	2.0658
	(-0.73)	(-0.62)	(-0.60)	(-0.58)	(1.55)	(1.68)	(1.38)	(1.32)
US_MKT	-0.4791**	-0.4504**	-0.4578**	-0.4502**	-0.5022	-0.3884	-0.3892	-0.4282
	(-2.33)	(-2.18)	(-2.21)	(-2.18)	(-0.45)	(-0.33)	(-0.40)	(-0.44)
TREASURY_MKT	4.3715	4.1825	3.9433	4.0660	22.3284	24.1035	24.2505	21.9766
	(1.03)	(1.01)	(0.91)	(0.96)	(0.90)	(0.95)	(1.34)	(1.21)
VOLRISK_PREM	-0.2248***	-0.2249***	-0.2226***	-0.2234***	-0.6996*	-0.6989*	-0.3568	-0.3474
	(-3.67)	(-3.64)	(-3.55)	(-3.53)	(-1.71)	(-1.67)	(-0.95)	(-0.94)
ADS_INDEX	0.0074	0.0103	0.0087	0.0092	0.2800	0.2643	-0.2609	-0.2575
	(0.08)	(0.11)	(0.09)	(0.09)	(0.56)	(0.52)	(-0.59)	(-0.59)
INTERCEPT	-0.0115	-0.0071	-0.0245	-0.0147	0.1364*	0.1562**	-0.0349	-0.0963
	(-0.49)	(-0.30)	(-1.05)	(-0.58)	(1.83)	(2.05)	(-0.64)	(-1.22)
N	323	323	323	323	323	323	323	323
Adj. R^2	0.21	0.22	0.22	0.22	0.34	0.35	0.51	0.52

Table 10. Robustness Test 2

This table presents the anatomy analysis of credit action reports released by Moody's from 2003 to 2013 for the "predicted" and "surprise" components. POS_P and NEG_P are the positive and negative "predicted" components from Table 4, while POS_S and NEG_S are the positive and negative "surprise" components. The dependent variable is 3-day cumulative abnormal CDS(-1,1) in Models 1 to 4, and the dummy variable is 1-YEAR FUTURE DOWNGRADE in Models 5 to 8. For definitions of key variables, refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	CDS(-1,1)				1-yer Future Downgrade			
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
POS_P	-0.2023***	-0.2037***	-0.2261***	-0.2346***	-0.2490	0.0868	0.2089	0.3164
	(-2.82)	(-2.77)	(-2.60)	(-2.61)	(-0.69)	(0.28)	(0.46)	(0.81)
NEG_P	-0.0382	-0.0358	-0.0715	-0.0651	1.1795***	0.5581**	1.4242***	0.7186**
	(-0.74)	(-0.62)	(-1.28)	(-1.09)	(4.43)	(2.18)	(4.56)	(2.47)
POS_S	0.0272	0.0363	0.0278	0.0314	-0.4588***	-0.0601	-0.4480***	-0.0645
	(0.79)	(1.04)	(0.83)	(0.92)	(-3.66)	(-0.58)	(-3.52)	(-0.60)
NEG_S	0.0663**	0.0733**	0.0590*	0.0675**	0.4657***	0.1556	0.4999***	0.2021
	(2.12)	(2.20)	(1.95)	(2.18)	(3.26)	(1.11)	(3.42)	(1.40)
UP	-0.0189**	-0.0117	-0.0154*	-0.0048	-0.0420*	0.0704*	-0.0417	0.0740*
	(-2.15)	(-1.00)	(-1.69)	(-0.40)	(-1.78)	(1.78)	(-1.63)	(1.83)
DOWN	-0.0152	-0.0123	-0.0128	-0.0093	-0.1356*	0.0550	-0.1177	0.0573
	(-1.29)	(-0.86)	(-1.22)	(-0.71)	(-1.84)	(0.69)	(-1.57)	(0.71)
POS_WATCH		0.0106		0.0061		0.0272		0.0270
		(0.80)		(0.49)		(1.23)		(1.10)
NEG_WATCH		0.0038		0.0027		0.4700***		0.4691***
		(0.24)		(0.19)		(5.39)		(5.26)
POS_OUTLOOK		0.0044		0.0122		0.0689*		0.0708*
		(0.35)		(0.96)		(1.85)		(1.83)
NEG_OUTLOOK		0.0057		0.0075		0.2913***		0.2716***
		(0.41)		(0.54)		(3.96)		(3.64)
INITIAL_STATUS			0.0098	0.0108			-0.0777*	-0.0449
			(1.09)	(1.16)			(-1.65)	(-1.08)
RISING_STAR			-0.0031	-0.0040			0.0624*	0.0106
			(-0.21)	(-0.26)			(1.85)	(0.40)
FALLEN_ANGEL			0.0322	0.0323			-0.2273	-0.1198
			(1.20)	(1.18)			(-1.57)	(-0.81)
LOCAL_MKT			-0.4969***	-0.5079***			-1.3661	-1.1293
			(-2.77)	(-2.78)			(-1.50)	(-1.43)
FX_RATE			-0.1773	-0.1587			2.5958	2.0770
			(-0.68)	(-0.60)			(1.55)	(1.30)
US_MKT			-0.4896**	-0.4905**			-0.3001	-0.3712
			(-2.38)	(-2.40)			(-0.25)	(-0.38)
TREASURY_MKT			5.3592	5.1532			22.1496	20.5273
			(1.25)	(1.17)			(0.87)	(1.13)
VOLRISK_PREM			-0.1966***	-0.1943***			-0.6795	-0.3555
			(-3.14)	(-3.04)			(-1.64)	(-0.96)
ADS_INDEX			-0.0059	-0.0061			0.2545	-0.2331
			(-0.06)	(-0.06)			(0.49)	(-0.53)
INTERCEPT	0.1085**	0.1001**	0.1216**	0.1103**	-0.0678	-0.2507	-0.3059	-0.3732
	(2.37)	(2.10)	(2.34)	(2.09)	(-0.30)	(-1.27)	(-1.14)	(-1.60)
N	323	323	323	323	323	323	323	323
Adj. R^2	0.10	0.11	0.24	0.24	0.35	0.51	0.37	0.52

Table 11. Robustness Test 3

This table presents the anatomy analysis of rating reports in the expanded credit action reports released by Moody's from 2003 to 2013 (N=323) for specific content. Models 1 to 5 present the results for five content categories. The positive and negative tone related to each of these specific content categories are represented by CONTENT_POS and CONTENT_NEG. POS_RES and NEG_RES are the residual positive and negative tone related to other content. The dependent variable is CDS(-1,1), which is the 3-day cumulative abnormal CDS spread percentage change, calculated as the CDS spread percentage change of the sovereign country in excess of the market CDS spread percentage change. For definitions of key variables, refer to Table A1. The *t*-statistics are calculated based on robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Macroeconomic	(2) Public & External Finance	(3) Debt Dynamics	(4) Financial Sector	(5) Political & Institutional
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
POS_RES	0.0182	-0.0014	-0.0024	-0.0022	0.0008
	(0.42)	(-0.03)	(-0.06)	(-0.06)	(0.02)
NEG_RES	0.0482	0.0734**	0.0456	0.0646*	0.0642*
	(1.22)	(2.21)	(1.43)	(1.83)	(1.96)
CONTENT_POS	-0.0350	0.0092	0.0358	0.1228	0.0091
	(-0.83)	(0.18)	(0.63)	(1.09)	(0.11)
CONTENT_NEG	0.0785*	-0.0324	0.1180*	0.0474	0.0155
	(1.94)	(-0.52)	(1.86)	(0.80)	(0.16)
DOWN	-0.0038	-0.0049	-0.0058	-0.0036	-0.0054
	(-0.31)	(-0.40)	(-0.47)	(-0.28)	(-0.45)
NEG_WATCH	0.0048	0.0045	0.0014	0.0060	0.0036
	(0.33)	(0.33)	(0.10)	(0.42)	(0.26)
POS_OUTLOOK	0.0163*	0.0140	0.0141	0.0153	0.0132
	(1.72)	(1.46)	(1.46)	(1.60)	(1.31)
NEG_OUTLOOK	0.0089	0.0062	0.0109	0.0079	0.0099
	(0.65)	(0.46)	(0.86)	(0.57)	(0.75)
INITIAL_STATUS	-0.0041	-0.0012	-0.0051	-0.0027	-0.0012
	(-0.50)	(-0.15)	(-0.60)	(-0.35)	(-0.17)
RISING_STAR	-0.0019	-0.0059	-0.0041	-0.0035	-0.0054
	(-0.13)	(-0.40)	(-0.28)	(-0.24)	(-0.36)
FALLEN_ANGEL	0.0271	0.0259	0.0210	0.0289	0.0262
	(1.00)	(0.96)	(0.72)	(1.06)	(0.94)
LOCAL_MKT	-0.5532***	-0.5405***	-0.5194***	-0.5455***	-0.5431***
	(-3.05)	(-3.03)	(-2.85)	(-2.90)	(-3.03)
FX_RATE	-0.1552	-0.1453	-0.1943	-0.1479	-0.1583
	(-0.58)	(-0.54)	(-0.72)	(-0.53)	(-0.60)
US_MKT	-0.4503**	-0.4450**	-0.4689**	-0.4606**	-0.4438**
	(-2.19)	(-2.13)	(-2.28)	(-2.29)	(-2.23)
TREASURY_MKT	3.5780	4.1209	4.6468	3.8125	4.5296
	(0.84)	(0.98)	(1.10)	(0.89)	(1.03)
VOLRISK_PREM	-0.2201***	-0.2260***	-0.2217***	-0.2168***	-0.2270***
	(-3.52)	(-3.54)	(-3.48)	(-3.26)	(-3.48)
ADS_INDEX	0.0175	0.0211	0.0153	0.0033	0.0050
	(0.18)	(0.22)	(0.16)	(0.03)	(0.05)
INTERCEPT	-0.0192	-0.0205	-0.0219	-0.0237	-0.0216
	(-0.78)	(-0.81)	(-0.90)	(-0.96)	(-0.87)
N	323	323	323	323	323
Adj. R^2	0.22	0.22	0.22	0.22	0.22

Figure 1: Mean Net Tone for Moody's Credit Rating Reports

This figure presents the mean net tone scores in Moody's credit rating reports sorted by three types of rating action reports: the net tone of upgrade (UP) and downgrade (DOWN) reports in a sample of 166 rating reports, the net tone of positive (POS WATCH) and negative watch (NEG WATCH) reports in a sample of 68 watchlist reports, and the net tone of positive (POS OUTLOOK) and negative outlook (NEG OUTLOOK) reports in a sample of 89 outlook reports.

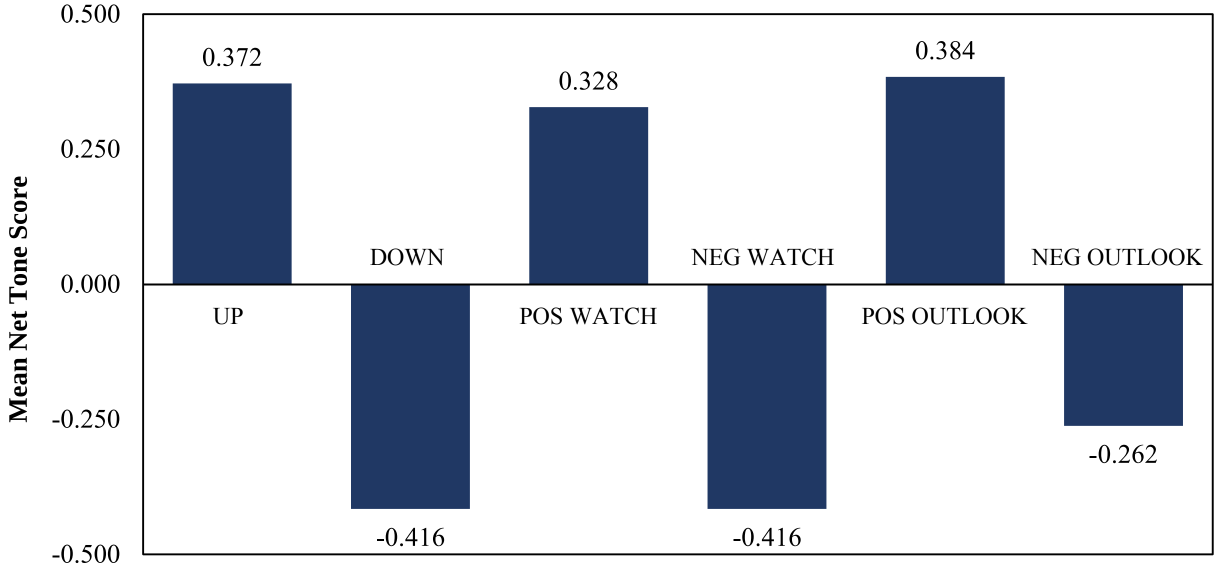
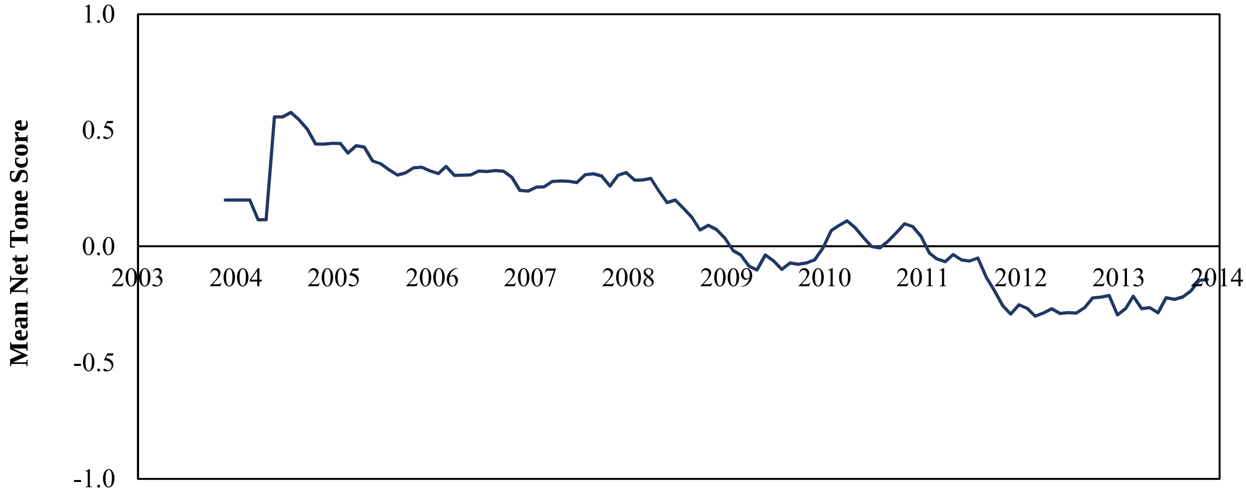


Figure 2: Variation in Mean Monthly Net Tone of Moody's Credit Rating Reports

This figure plots the 12-month moving average of the variation in mean monthly net tone scores of 166 credit rating reports issued by Moody's from 2003 to 2013.



APPENDIX A

Table A1: Definitions of Key Variables

This table presents definitions of the key dependent, independent, and tone variables used in our study.

Key Dependent Variables	
CDS(-1,1)	The 3-day cumulative abnormal CDS spread percentage change, calculated as the CDS spread percentage change of the sovereign in excess of the market CDS spread percentage change. The market CDS spread percentage change is based on an equal-weighted CDS index of all non-event countries in our sample.
1-YR FUTURE DOWNGRADE	A dummy variable that equals 1 if there is a downgrade within one year after the current rating action and 0 otherwise.
Key Tone Variables	
POS	The positive tone score, as measured by the percentage of positive sentences in the credit rating report.
NEG	The negative tone score, as measured by the percentage of negative sentences in the credit rating report.
Key Independent Variables	
UP	A dummy variable that equals 1 if there is a rating upgrade and 0 otherwise.
DOWN	A dummy variable that equals 1 if there is a rating downgrade and 0 otherwise.
POS_WATCH	A dummy variable that equals 1 if the sovereign's credit watch status is positive and 0 otherwise.
NEG_WATCH	A dummy variable that equals 1 if the sovereign's credit watch status is negative and 0 otherwise.
POS_OUTLOOK	A dummy variable that equals 1 if the sovereign's credit outlook status is positive and 0 otherwise.
NEG_OUTLOOK	A dummy variable that equals 1 if the sovereign's credit outlook status is negative and 0 otherwise.
INITIAL_STATUS	A dummy variable that equals 1 if the initial rating of the firm is below investment grade and 0 otherwise.
RISING_STAR	A dummy variable that equals 1 when a rating changes from speculative grade to investment grade and 0 otherwise.
FALLEN_ANGEL	A dummy variable that equals 1 when a rating changes from investment grade to speculative grade and 0 otherwise.
LOCAL_MKT	The local stock market return (denominated in U.S. dollars), calculated from the local MSCI index or, if unavailable, a local stock market index.
FX_RATE	The percentage change in the exchange rate of the local currency against the dollar.

US_MKT	The U.S. stock market excess return, calculated as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill return.
TREASURY_MKT	The change in Treasury yields, based on the five-year constant maturity Treasury (CMT) rates.
VOLRISK_PREM	The change in the volatility risk premium, which is calculated as the difference between the VIX index and a measure of realized volatility for the S&P 100 index. The measure of realized volatility for date t is based on the Garman-Klass (1980) open-high-low-close volatility estimator applied to the corresponding data for the S&P 100 index for the 20-day period from date $t - 19$ to t.
ADS_INDEX	The change in the Aruoba-Diebold-Scotti business conditions index, which is designed to track real business conditions in the U.S. at a high frequency (daily).
INITIAL_RATING	The credit rating before the current rating change announcement. Alphabetic ratings are converted into numerical values from 1 to 22, which represent Aaa to D on Moody's rating scale.
RECENT_DEFAULT	A dummy variable that equals 1 if a credit rating has been at or close to default (defined to be Caa1 and below on Moody's rating scale) within the past two years and 0 otherwise.
GDP_GROWTH	The annual real GDP growth of the sovereign for the year prior to the current rating action.
DEBT_GDP	The debt to GDP ratio of the sovereign for the year prior to the current rating action.
FRES_GDP	The ratio of foreign reserves to GDP of the sovereign for the year prior to the current rating action.
FRES_GROWTH	The annual foreign reserves growth of the sovereign for the year prior to the current rating action.
FX_GROWTH	The annual percentage change in the exchange rate of the local currency against the dollar for the year prior to the current rating action.
TRADEBAL_GDP	The ratio of the trade balance to GDP of the sovereign country for the year prior to the current rating action.
SP500	The monthly return of the S&P 500 index for the month prior to the current rating action.
FISCAL_FREEDOM	A sub-index of the Index of Economic Freedom in the World provided by the Heritage Foundation that describes a country's governance practices related to fiscal practices and the tax burden.
MONETARY_FREEDOM	A sub-index of the Index of Economic Freedom in the World provided by the Heritage Foundation that describes a country's governance practices related to price stability and price controls.
FINANCIAL_FREEDOM	A sub-index of the Index of Economic Freedom in the World provided by the Heritage Foundation that describes the independence and efficiency of a country's financial sector.

HIGH_STRESS	An indicator of a high market stress period, measured by the probability that the VIX index is in a high volatility state (out of three possible states), estimated using a Markov regime-switching framework as described in Hamilton and Susmel (1994) and Gonzalez-Hermosillo and Hesse (2011).
POST2009	A dummy variable that equals 1 if the year of the current rating action is after 2009 (i.e., 2010 or later) and 0 otherwise.
Other Tone Variables	
CONTENT_POS CONTENT_NEG	Positive and negative tone associated with sentences classified under a specific content category. These include macroeconomic (MACRO), public & external finance (PEF), debt dynamics (DEBT), financial sector (FIN), and political & institutional (POL).
POS_RES NEG_RES	Positive and negative tone after accounting for the tone associated with a specific content category.
POS_S NEG_S	The surprise components of positive and negative tone, calculated as the difference between the actual tone score of the credit rating report and the tone score predicted by a model based on variables linked to sovereign default risk shown in Table 4.
POS_P NEG_P	The predicted components of positive and negative tone, estimated by the computation method described in Table 4.

Table A2: List of Countries Included

This table presents the list of 62 countries and the respective number of credit rating reports within each country that are included in our data sample. The 323 reports included in this study include credit rating changes, watchlists, and outlooks.

No.	Country	No of Reports		No.	Country	No of Reports
1	Argentina	3		32	Latvia	7
2	Austria	1		33	Lebanon	7
3	Bahrain	6		34	Lithuania	6
4	Belgium	3		35	Malaysia	3
5	Brazil	10		36	Malta	5
6	Bulgaria	8		37	Mexico	1
7	Chile	6		38	Morocco	1
8	China	4		39	Netherlands	1
9	Colombia	5		40	Pakistan	9
10	Costa Rica	3		41	Panama	4
11	Croatia	3		42	Peru	8
12	Cyprus	14		43	Philippines	11
13	Czech Republic	1		44	Portugal	8
14	Dominican Republic	1		45	Qatar	4
15	Egypt	9		46	Romania	4
16	El Salvador	4		47	Russia	5
17	Estonia	3		48	Saudi Arabia	1
18	France	2		49	Slovakia	7
19	Germany	1		50	Slovenia	8
20	Greece	12		51	South Africa	6
21	Guatemala	1		52	South Korea	6
22	Hong Kong	7		53	Spain	8
23	Hungary	8		54	Thailand	1
24	Iceland	8		55	Tunisia	1
25	Indonesia	12		56	Turkey	7
26	Ireland	8		57	Ukraine	9
27	Israel	3		58	United Kingdom	2
28	Italy	4		59	United States	2
29	Jamaica	6		60	Uruguay	6
30	Japan	6		61	Venezuela	4
31	Kazakhstan	4		62	Vietnam	5
Total		**166**		**Total**		**157**

Table A3: Summary Statistics

	N	Mean	Median	Std Dev	Min	Max
Key Dependent Variables						
CDS(-1,1)	323	0.0097	0.0004	0.0693	-0.1852	0.2748
1-YR FUTURE DOWNGRADE	323	0.2229	0.0000	0.4168	0.0000	1.0000
Key Independent Variables						
POS	323	0.3765	0.3529	0.2059	0.0000	1.0000
NEG	323	0.3654	0.3333	0.2467	0.0000	0.9375
UP	323	0.2477	0.0000	0.4323	0.0000	1.0000
DOWN	323	0.2663	0.0000	0.4427	0.0000	1.0000
POS_WATCH	323	0.1176	0.0000	0.3227	0.0000	1.0000
NEG_WATCH	323	0.1269	0.0000	0.3334	0.0000	1.0000
POS_OUTLOOK	323	0.3344	0.0000	0.4725	0.0000	1.0000
NEG_OUTLOOK	323	0.4087	0.0000	0.4924	0.0000	1.0000
INITIAL_STATUS	323	0.4180	0.0000	0.4940	0.0000	1.0000
RISING_STAR	323	0.0341	0.0000	0.1817	0.0000	1.0000
FALLEN_ANGEL	323	0.0248	0.0000	0.1557	0.0000	1.0000
LOCAL_MKT	323	-0.0010	-0.0008	0.0320	-0.2361	0.1808
FX_RATE	323	0.0012	0.0000	0.0159	-0.0945	0.2200
US_MKT	323	-0.0017	0.0003	0.0218	-0.1367	0.0644
TREASURY_MKT	323	0.0000	-0.0001	0.0009	-0.0025	0.0037
VOLRISK_PREM	323	-0.0043	-0.0013	0.0485	-0.3798	0.3108
ADS_INDEX	323	0.0011	-0.0007	0.0433	-0.1278	0.1671
INITIAL_RATING	323	13.8947	13.0000	4.4702	2.0000	22.0000
RECENT_DEFAULT	323	0.0372	0.0000	0.1894	0.0000	1.0000
GDP_GROWTH	323	0.0359	0.0402	0.0436	-0.0776	0.2617
DEBT_GDP	323	0.5764	0.5020	0.3891	0.0369	1.9332
FRES_GDP	323	0.1218	0.0819	0.1293	0.0012	0.9076
FRES_GROWTH	323	0.1779	0.0987	0.4224	-0.5562	3.5224
FX_GROWTH	323	-0.0041	-0.0012	0.0784	-0.2816	0.4058
TRADEBAL_GDP	323	-0.0365	-0.0401	0.1325	-0.3683	0.4183
SP500	323	0.0022	0.0078	0.0471	-0.1694	0.1077
FISCAL_FREEDOM	323	75.4263	75.3000	11.0218	42.1000	99.9000
MONETARY_FREEDOM	323	76.6570	77.6000	7.5078	46.1000	94.3000
FINANCIAL_FREEDOM	323	58.1424	60.0000	16.8189	20.0000	90.0000
HIGH_STRESS	323	0.1407	0.0012	0.3129	0.0000	1.0000
POST2009	323	0.4706	0.0000	0.4999	0.0000	1.0000
Other Tone Variables						
MACRO_POS	323	0.1670	0.1522	0.1188	0.0000	0.5600
MACRO_NEG	323	0.1251	0.0952	0.1150	0.0000	0.4231
PEF_POS	323	0.0807	0.0625	0.0813	0.0000	0.4167
PEF_NEG	323	0.0509	0.0385	0.0580	0.0000	0.2727
DEBT_POS	323	0.0672	0.0526	0.0802	0.0000	0.5000
DEBT_NEG	323	0.0740	0.0556	0.0916	0.0000	0.6111
FIN_POS	323	0.0145	0.0000	0.0322	0.0000	0.2222
FIN_NEG	323	0.0410	0.0000	0.0722	0.0000	0.4483
POL_POS	323	0.0219	0.0000	0.0444	0.0000	0.2500
POL_NEG	323	0.0412	0.0000	0.0672	0.0000	0.4375

Table A4: Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	POS	-															
		-															
(2)	NEG	-0.79***	-														
		(0.00)	-														
(3)	UP	0.45***	-0.46***	-													
		(0.00)	*(0.00)*	-													
(4)	DOWN	-0.53***	0.61***	-0.35***	-												
		(0.00)	*(0.00)*	*(0.00)*	-												
(5)	POS_WATCH	0.14*	-0.35***	-0.21***	-0.22***	-											
		(0.01)	*(0.00)*	*(0.00)*	*(0.00)*	-											
(6)	NEG_WATCH	-0.40***	0.35***	-0.22***	0.00	-0.14*	-										
		(0.00)	*(0.00)*	*(0.00)*	*(0.97)*	*(0.01)*	-										
(7)	POS_OUTLOOK	0.50***	-0.61***	-0.12*	-0.43***	0.52***	-0.27***	-									
		(0.00)	*(0.00)*	*(0.03)*	*(0.00)*	*(0.00)*	*(0.00)*	-									
(8)	NEG_OUTLOOK	-0.69***	0.77***	-0.48***	0.41***	-0.30***	0.46***	-0.59***	-								
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	-								
(9)	INITIAL_STATUS	0.20***	-0.10	0.12*	-0.08	0.04	-0.08	0.05	-0.18**	-							
		(0.00)	*(0.06)*	*(0.03)*	*(0.13)*	*(0.46)*	*(0.16)*	*(0.36)*	*(0.00)*	-							
(10)	RISING_STAR	0.21***	-0.15**	0.33***	-0.11*	-0.07	-0.07	-0.02	-0.16**	0.22***	-						
		(0.00)	*(0.01)*	*(0.00)*	*(0.04)*	*(0.22)*	*(0.20)*	*(0.66)*	*(0.00)*	*(0.00)*	-						
(11)	FALLEN_ANGEL	-0.16**	0.21***	-0.09	0.26***	-0.06	-0.06	-0.11*	0.11*	-0.14*	-0.03	-					
		(0.00)	*(0.00)*	*(0.10)*	*(0.00)*	*(0.30)*	*(0.28)*	*(0.04)*	*(0.05)*	*(0.02)*	*(0.59)*	-					
(12)	LOCAL_MKT	0.04	-0.06	0.04	0.01	-0.00	-0.07	0.08	-0.06	-0.01	0.04	-0.02	-				
		(0.45)	*(0.25)*	*(0.42)*	*(0.85)*	*(0.95)*	*(0.24)*	*(0.15)*	*(0.28)*	*(0.90)*	*(0.44)*	*(0.74)*	-				
(13)	FX_RATE	0.03	-0.03	0.04	0.06	-0.06	-0.06	-0.02	0.01	-0.00	0.04	-0.03	0.64***	-			
		(0.58)	*(0.56)*	*(0.45)*	*(0.31)*	*(0.30)*	*(0.31)*	*(0.72)*	*(0.89)*	*(0.99)*	*(0.49)*	*(0.58)*	*(0.00)*	-			
(14)	US_MKT	0.07	-0.05	0.10	0.01	0.00	-0.04	0.04	-0.12*	0.12*	0.05	0.01	0.37***	0.22***	-		
		(0.21)	*(0.33)*	*(0.07)*	*(0.87)*	*(0.94)*	*(0.51)*	*(0.49)*	*(0.03)*	*(0.03)*	*(0.40)*	*(0.85)*	*(0.00)*	*(0.00)*	-		
(15)	TREASURY_MKT	-0.02	-0.00	-0.03	0.08	0.07	0.01	0.05	-0.04	0.02	0.06	0.01	0.07	0.04	0.31***	-	
		(0.67)	*(0.96)*	*(0.56)*	*(0.14)*	*(0.21)*	*(0.91)*	*(0.38)*	*(0.44)*	*(0.66)*	*(0.27)*	*(0.90)*	*(0.23)*	*(0.42)*	*(0.00)*	-	
(16)	VOLRISK_PREM	*0.08*	*-0.07*	*0.05*	*-0.04*	*0.04*	*-0.09*	*0.07*	*-0.11**	*0.01*	*0.06*	*-0.01*	*-0.05*	*-0.05*	*0.09*	*0.13**	-
		(0.15)	*(0.20)*	*(0.39)*	*(0.47)*	*(0.49)*	*(0.10)*	*(0.19)*	*(0.05)*	*(0.80)*	*(0.32)*	*(0.91)*	*(0.39)*	*(0.35)*	*(0.12)*	*(0.02)*	-
(17)	ADS_INDEX	-0.03	-0.01	0.03	-0.04	0.02	0.13*	-0.05	0.02	-0.02	-0.04	0.04	-0.06	-0.10	-0.04	0.02	0.07
		(0.65)	*(0.89)*	*(0.65)*	*(0.46)*	*(0.77)*	*(0.02)*	*(0.42)*	*(0.75)*	*(0.72)*	*(0.43)*	*(0.43)*	*(0.28)*	*(0.06)*	*(0.44)*	*(0.72)*	*(0.21)*

APPENDIX B

1. Greece (29 November 2013)

Rating Action: Moody’s upgrades Greece’s government bond rating to Caa3 from C; stable outlook

London, 29 November 2013 -- Moody's Investors Service has today upgraded Greece's government bond rating to Caa3 from C. The outlook on the rating is now stable. The short term ratings remain Not Prime (NP).

The upgrade reflects the combination of the following key drivers:

(1) The significant fiscal consolidation that has taken place under Greece's structural adjustment program despite low growth and political uncertainty. As a result, Moody's expects that the government will achieve (and possibly outperform) its target of a primary balance in 2013, and record a surplus in 2014 in accordance with the adjustment program.

(2) The improvement in Greece's medium-term economic outlook supported by a cyclical recovery in the economy and also the progress made in implementing structural reforms and rebalancing the economy.

(3) The significant reduction of the government's interest burden following previous restructurings and official sector repayment assistance.

The key drivers taken together reduce the likelihood of further Private Sector Involvement (PSI) being undertaken as a condition for further financing.

Concurrently, Moody's has today raised the local and foreign-currency ceiling of Greece to B3 from Caa2.

RATINGS RATIONALE
RATIONALE FOR UPGRADE

The first driver behind Moody's upgrade of Greece's rating is the government's progress in fiscal consolidation under the Troika-supported program, which has led to a 74% (or 11.6% of GDP) decline in its headline deficit since 2009. Based on the government's budget execution record up until October, Moody's believes that the government's deficit target (4.1% under the Troika support program, 13.5% of GDP according to Eurostat's definition, which also includes bank recapitalization costs) is likely to be within reach. Moreover, the government's recently presented 2014 budget envisages a further reduction in the general government deficit, which remains in line with targets under the Troika support program.

Moody's recognizes that the 2014 budget balances the fragile social and political environment in the country with the country's commitment to its international creditors. As a result, the rating agency expects the focus of the budget will remain on savings generated from structural reform measures as opposed to further expenditure cuts. That being said, Moody's believes that the government remains committed to achieving a primary surplus of close to 1.5% of GDP in 2014, especially as this will be required to qualify for continuing debt reduction from official creditors.

The second driver behind the upgrade is the evidence that the Greek economy is bottoming out after nearly six years of recession and that the combination of cyclical factors and the implementation of structural reforms are leading to a gradual improvement in medium-term growth prospects. Over the near term, the rating agency expects only a modest contraction of 0.5% in 2014 before the Greek economy records growth of 1% in 2015. Net exports will remain the near-term growth driver of the economy (led by tourism receipts) supported by a deceleration in consumption and investment growth. Although private investments remain fragile and weak, public investments continue to be supported with the disbursements and greater absorption of EU structural funds.

Looking further ahead, the rebalancing of the economy continues, with Moody's expecting the current account to shrink to a deficit of 0.5% of GDP in 2013 from an average deficit of around 10% over the previous five years. In addition, sentiment indicators -- namely industrial confidence surveys as well as indicators for the service industry -- illustrate a significant upward improvement in business expectations for the next 12 months.

The third driver of today's rating action is Greece's significantly reduced interest burden, resulting from the compositional change in the country's debt profile following two defaults on private-sector debt and as a result of the official-sector repayment assistance. Moody's expects that, as at year-end 2013, approximately 83% of Greece's general government debt will be owed to the official sector (mainly the IMF, EU and the ECB and euro area governments), with the balance accounted for by domestic banks and other private sector creditors.

Key debt metrics have improved as a result of this new creditor structure. Greece's debt-affordability ratio (general government interest expenses as a percentage of revenues) has decreased to an estimated 9.2% in 2013 from 17.0% in 2011, and interest as a percentage of GDP at around 4% of GDP is now consistent with other countries in the euro area. Greece's debt-maturity profile has also been lengthened to around 17 years in 2013, from around
6.5 years in 2011. Moody's does caution, however, that Greece's substantial debt stock (estimated at 175% of GDP in 2013) continues to weigh on its solvency. Although the rating agency expects debt to peak next year and then to fall from 2015 onwards, the overall reduction will be gradual and will remain susceptible to nominal growth shocks and policy implementation risks.

The very significantly diminished share of privately held debt may also weaken the rationale for a new round of PSI in order to improve Greece's debt profile. This assessment balances the limited financial benefits to Greece's supporters with their incentive for the country to regain access to the private debt markets as quickly as possible.

However, Moody's notes that the above-mentioned credit positive drivers are balanced by Greece's still large debt burden and the expectation that the current political environment will prove challenging in terms of negotiations with official creditors (as reflected in the latest negotiations on the 2014 budget). As a result, the rating remains at a low level to reflect the associated risks to the few remaining private-sector creditors.

RATIONALE FOR RAISING LOCAL AND FOREIGN-CURRENCY CEILING

Moody's has raised the local and foreign-currency ceiling of Greece to B3 from Caa2. Notwithstanding a fragile and unpredictable domestic political environment, the B3 country risk ceiling reflects a slightly lower redenomination risk and a lower likelihood of exit from the euro area as a result of a slowly improving economy, improved debt affordability and continued euro area support as the country achieves its targets under the Troika program.

WHAT COULD MOVE THE RATING UP/DOWN

Moody's could consider upgrading the rating in the event of a combination of (1) an easing of political uncertainty; (2) a continuation of structural reforms which would support long-term economic growth; and (3) sustained primary surpluses, which would support a continued decline in debt levels.

Conversely, the rating could be downgraded if there is a deceleration in the implementation of the Troika economic program due to heightened political risk and reform fatigue, as this would further hinder Greece's growth prospects and its ability to generate large primary surpluses over the coming years.

GDP per capita (PPP basis, US$): 24,260 (2012 Actual) (also known as Per Capita Income)

Real GDP growth (% change): -6.4% (2012 Actual) (also known as GDP Growth)

Inflation Rate (CPI, % change Dec/Dec): 0.8% (2012 Actual)

Gen. Gov. Financial Balance/GDP: -9% (2012 Actual) (also known as Fiscal Balance)

Current Account Balance/GDP: -2.4% (2012 Actual) (also known as External Balance)

External debt/GDP: [not available]

Level of economic development: Low level of economic resilience

Default history: At least one default event (on bonds and/or loans) has been recorded since 1983.

On 25 November 2013, a rating committee was called to discuss the rating of the Greece, Government of. The main points raised during the discussion were: The issuer's economic fundamentals, including its economic strength, have materially increased. The issuer's fiscal or financial strength, including its debt profile, has materially increased. The issuer has become less susceptible to event risks, particularly contingent liabilities emanating from the banking sector. However, the political environment in Greece continues to be fragile. The principal methodology used in this rating was Sovereign Bond Ratings published in September 2013. Please see the Credit Policy page on www.moodys.com for a copy of this methodology.

The weighting of all rating factors is described in the methodology used in this rating action, if applicable.

(Positive: 0.3902; Negative: 0.4634; Neutral: 0.1464)

2. United States (02 August 2011)

Rating Action: Moody’s confirms US Aaa Rating, assigns negative outlook

New York, August 02, 2011 -- Moody's Investors Service has confirmed the Aaa government bond rating of the United States following the raising of the statutory debt limit on August 2. The rating outlook is now negative.

Moody's placed the rating on review for possible downgrade on July 13 due to the small but rising probability of a default on the government's debt obligations because of a failure to increase the debt limit. The initial increase of the debt limit by $900 billion and the commitment to raise it by a further $1.2-1.5 trillion by yearend have virtually eliminated the risk of such a default, prompting the confirmation of the rating at Aaa.

In confirming the Aaa rating, Moody's also recognized that today's agreement is a first step toward achieving the long-term fiscal consolidation needed to maintain the US government debt metrics within Aaa parameters over the long run. The legislation calls for $917 billion in specific spending cuts over the next decade and established a congressional committee charged with making recommendations for achieving a further $1.5 trillion in deficit reduction over the same time period. In the absence of the committee reaching an agreement, automatic spending cuts of $1.2 trillion would become effective.

In assigning a negative outlook to the rating, Moody's indicated, however, that there would be a risk of downgrade if (1) there is a weakening in fiscal discipline in the coming year; (2) further fiscal consolidation measures are not adopted in 2013; (3) the economic outlook deteriorates significantly; or (4) there is an appreciable rise in the US government's funding costs over and above what is currently expected.

First, while the combination of the congressional committee process and automatic triggers provides a mechanism to induce fiscal discipline, this framework is untested. Attempts at fiscal rules in the past have not always stood the test of time. Therefore, should the new mechanism put in place by the Budget Control Act prove ineffective, this could affect the rating negatively. Moody's baseline scenario assumes that fiscal discipline is maintained in 2012, despite pressures for fiscal relaxation that often precede general elections and the difficult negotiations that are likely to arise due to the scheduled expiration of the so-called "Bush tax cuts" at the end of that year.

Second, further measures will likely be required to ensure that the long-run fiscal trajectory remains compatible with an Aaa rating. Specifically, Moody's expects to see a stabilization of the federal government's debt-to-GDP ratio not too far above its projected 2012 level of 73% by the middle of the decade, followed by a decline. Such a pattern would also support a smaller interest burden as a percentage of government revenues than is now projected. Wide political differences that have characterized the recent debt and fiscal debate, if they continue, could prevent effective policymaking around that time. Measures that further reduce long-term deficits would be positive for the rating; a lack of such measures would be negative.

Third, recent downward revisions of economic growth rates and the very low growth rate recorded in the first half of 2011 call into question the strength of potential growth in the coming year or two. Continued very low growth would make fiscal consolidation more difficult. As a result, Moody's will also be monitoring the pace of growth as it relates to the fiscal effort.

Finally, the US Treasury's cost of borrowing has remained low despite the recent political uncertainties surrounding the debt limit and the long-term fiscal outlook. While Moody's and economic forecasters generally expect interest rates to rise over the next few years, a rise in borrowing costs above and beyond what is now expected would threaten efforts at fiscal consolidation. Such a development would also be negative for the rating should it occur.

Moody's has also confirmed the Aaa ratings of certain US government-guaranteed bonds issued by the governments of Israel and Egypt, which had been on review for possible downgrade as a result of the review of the US government's bond rating.

(Positive: 0.1667; Negative: 0.6250; Neutral: 0.2083)

APPENDIX C

In our study, each sentence in each sovereign credit rating report is classified on two dimensions. The first is tone, which comprises three categories: positive, negative, and neutral. The second is content, which comprises six categories based on sovereign credit rating indicators used by Moody's: macroeconomic, public & external finance, debt dynamics, financial sector, political & institutional, and others. A description of these content categories is provided in Table C1.

[Insert Table C1 here]

We first download credit rating reports from Moody's Sovereign & Supranational Research & Ratings database from 2003 to 2013. We then remove the header, footer, 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. To construct our training dataset, we manually classify 2,000 randomly selected sentences according to the tone and content dimensions. Panel A in Table C2 reports the breakdown of the training dataset. 40.0% of sentences are classified as being of positive tone and 39.0% negative. The content categories macroeconomic, public & external finance, and debt dynamics comprise the largest proportions of sentences at 27.7%, 20.0%, and 16.9% respectively.

[Insert Table C2 here]

We use two established methods in the textual analysis literature to validate the performance of our algorithm. The first is the in-sample test, where we use the 2,000 manually coded sentences to train the classifier and test it with the same sample. The second is the 10-fold cross validation, where the sample of 2,000 sentences is randomly and evenly split into 10 subsets (folds) and the classifier is trained and tested 10 times. Each time, nine folds of data (out of the 10) are selected as the training data, and the remaining one fold is used to test the classifier. The average accuracy and false prediction rates are reported for both tests in Table C2 Panel B. The performance of our algorithm is robust, with accuracy rates of 86.7% and 69.3% for the in-sample test and 10-fold cross validation respectively, similar to those of Li (2010) and Huang, Zang, and Zheng (2012). Finally, Table C2 Panel C provides an analysis of our text classification results, which are discussed in the main text.

Table C1: Description of Content Categories in Credit Rating Reports Used in Naïve Bayesian Text Classification

This table presents a description of the content categories of credit rating reports used in our study. The content categories are based on the sovereign credit rating indicators used by the three major CRAs, adapted from Moody's (2013), Fitch (2011), Standard & Poor's (2011), and International Monetary Fund (2010). Sentences with information content that match the descriptions in this table are manually classified accordingly to form the training dataset for our Naïve Bayesian algorithm. The trained classifier then classifies sentences in the credit rating reports into one of the six categories.

Content	**Description**
Macroeconomic	Growth and volatility in GDP, output, employment, imports, exports Scale and competitiveness of economy Integration in economic and trade zones, spillover of risk Implementation of countercyclical macroeconomic policies Exchange rate regimes Indexation and dollarization

Public & External Finance	Balance of payments dynamics Structure of current account Foreign exchange reserves Access to foreign exchange Capital flows Financial assets of the government Government's ability to raise taxes, cut spending, sell assets, or obtain foreign currency Revenue-raising flexibility and efficiency Volatility of government revenue Expenditure effectiveness and pressures Impact of fiscal and monetary policies on external accounts External vulnerability indicators Size and health of nonfinancial public sector enterprises
Debt Dynamics	Level of debt, debt repayment burden, debt dynamics Interest payments Structure of government debt (maturity, interest rate, currency) Contingent liabilities of government Debt payment record of sovereign Depth and breath of local capital markets Access of concessional funding
Financial Sector	Strength and robustness of the financial sector Contingent liabilities of banking sector Quality of banking sector and supervision Foreign ownership of banking sector
Political & Institutional	War risk, political chaos Geopolitical risk and public security Relations with international community and institutions Orderliness of leadership succession Control of corruption Stability, legitimacy, and credibility of political institutions Transparency in economic policy decisions and objectives Strength of business environment, human capital, and governance Efficiency of public sector
Others	General descriptive statements with little information content on rating rationales or risk factors influencing rating actions This category acts as a catch-all for sentences that do not fit into one of the above-mentioned categories

Table C2: Naïve Bayesian Classification Training Dataset, Algorithm Accuracy, and Report-Level Analysis of Results

This table presents the dataset used to train the Naïve Bayesian classifier, a validation of the accuracy of the classifier for Moody's credit rating actions, and a report-level analysis of the classification results. Panel A reports the breakdown of the training dataset, which is composed of 2,000 sentences randomly extracted from Moody's credit rating reports and manually classified into tone and content categories. Stemming and stopwording processes are implemented 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. Stopwords, which include articles, case particles, conjunctions, pronouns, auxiliary verbs, and common prepositions, usually have only a grammatical function within a sentence and do not add meaning. Some examples of stopwords in the English language are: "the," "and," "it," "is," and "of." Panel B reports the results of the in-sample and 10-fold cross-validation tests, which are used to test the accuracy of the Naïve Bayesian classifier. For the in-sample test, we use 2,000 manually coded sentences to train the classifier and test the classifier with the same sample. In the 10-fold cross validation, the sample of 2,000 sentences is randomly and evenly split into 10 subsets (folds), and the classifier is trained and tested 10 times. Each time, nine folds of data (out of the 10) are selected as the training data, and the remaining one fold is used to test the classifier. Accuracy is measured as the number of correct classifications divided by the total number of sentences in the test sample. False positive (negative, neutral, macroeconomic, public & external finance, debt dynamics, financial sector, political & institutional, others) is defined as the number of sentences incorrectly predicted to be positive (negative, neutral, macroeconomic, public & external finance, debt dynamics, financial sector, political & institutional, others), divided by the total number of sentences in the test sample. The average accuracy and false prediction rates are reported for both the in-sample and 10-fold cross-validation tests. Panel C presents a report-level analysis of the sample of Moody's credit rating action reports used in this study.

Panel A: Training Dataset Breakdown

Tone categories	**Sentences**	**% of dataset**	**Content categories**	**Sentences**	**% of dataset**
Positive	799	40.0%	Macroeconomic	553	27.7%
Negative	779	39.0%	Public & External Finance	399	20.0%
Neutral	422	21.1%	Debt Dynamics	337	16.9%
			Financial Sector	215	10.8%
			Political & Institutional	328	16.4%
			Others	168	8.4%
Total	***2000***	***100.0%***	***Total***	***2000***	***100.0%***

Panel B: In-Sample and 10-Fold Cross Validation Test Results

	In-sample validation	10-fold cross validation
Tone category classification		
Accuracy	86.7%	69.3%
False Positive	6.2%	13.4%
False Negative	4.6%	11.9%
False Neutral	2.6%	5.4%
Total	***100.0%***	***100.0%***
Risk factor content category classification		
Accuracy	87.6%	67.8%
False Macroeconomic	5.5%	13.4%
False Public & External Finance	2.9%	7.9%
False Debt Dynamics	2.2%	5.7%
False Financial Sector	0.9%	1.9%
False Political & Institutional	0.7%	2.4%
False Others	0.4%	0.9%
Total	***100.0%***	***100.0%***

Panel C: Report-Level Analysis of Naïve Bayes Algorithm Results

Rating action / report type	Reports	Sentences	Sentence breakdown								
			POS	NEG	NEUT	MACRO	PEF	DEBT	FIN	POL	OTHERS
Credit Rating Changes	166	6038	28.9%	53.8%	17.3%	35.4%	10.6%	19.5%	8.2%	7.0%	19.4%
Credit Rating Changes and Watchlists	234	7407	29.2%	51.1%	19.7%	34.7%	11.2%	18.9%	8.1%	7.1%	19.9%
Credit Rating Changes, Watchlists and Outlooks	323	10278	30.3%	50.9%	18.8%	35.7%	11.4%	18.1%	8.2%	7.7%	18.9%

Rating action / report type	Reports	Tone scores								
		POS			NEG			NET_TONE		
		Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev
Credit rating changes										
Upgrades	80	0.539	0.529	0.115	0.168	0.156	0.107	0.372	0.375	0.173
Downgrades	86	0.197	0.185	0.088	0.613	0.617	0.139	-0.416	-0.413	0.210
Watchlists										
Positive watch	38	0.455	0.434	0.172	0.127	0.134	0.102	0.328	0.333	0.206
Negative watch	30	0.165	0.150	0.077	0.581	0.577	0.125	-0.416	-0.443	0.162
Outlooks										
Positive outlook	51	0.565	0.577	0.172	0.181	0.176	0.127	0.384	0.400	0.261
Negative outlook	38	0.274	0.272	0.120	0.536	0.561	0.131	-0.262	-0.261	0.237