The Information Value of Sovereign Credit Rating Reports

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ABSTRACT

We examine the information value of sovereign credit rating reports issued by Moody's in the sovereign credit default swaps (CDS) markets across 70 countries from 2003 to 2013. We find that the negative linguistic tone in the reports contains new information beyond credit rating actions. We code the sentences in each report into six broad content categories and find that the most informative sentences are related to negative debt dynamics. Interestingly, the financial sector related sentences have lost their informativeness after the 2009 Eurozone debt crisis. Overall, our study reveals novel evidence that sovereign credit rating reports contain valuable default-related information.

JEL Classification: G12, G14, G15

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1. INTRODUCTION

The recent Eurozone sovereign debt crisis has highlighted the economic importance of sovereign credit ratings and its relation to the sovereign default risk (e.g., Ramadorai, 2010). However, the extant literature has mainly focused on the impact of sovereign rating actions on capital markets (e.g., Almeida, Cunha, Ferreira, and Restrepo, 2014) and no study so far has examined other information provided by credit rating agencies (CRAs) such as the sovereign credit rating reports released concurrently with the rating announcements. Our study fills this void by exploring the information content of sovereign credit rating reports in sovereign credit default swaps (CDS) markets.

Exploring sovereign credit rating reports is interesting for two reasons. First, the economic consequence of sovereign credit rating actions can be huge as they affect the efficiency and stability of capital markets within and across countries.[1] The sovereign credit rating reports contain the detailed default-related reasoning for the rating actions. It will be useful for investors and regulators to fully understand the information provided by CRAs behind these important country-level rating actions.

Second, the incentives faced by CRAs in providing sovereign credit ratings can be very different from those in providing corporate credit ratings or those faced by stock analysts in providing corporate-related information (e.g., Agarwal, Chen and Zhang, 2015; Merkley, Michaely and Pacelli, 2013). For example, a significant number of sovereign credit ratings are unsolicited and as a result, the quality of sovereign credit ratings issued by CRAs may be of concern because of the lack of proper incentives (European Securities and Markets

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[1] The literature has studied the impact of sovereign credit rating changes on capital markets (Brooks, Faff, Hillier, and Hillier, 2004; Ismailescu and Kazemi, 2010; Afonso, Furceri, and Gomes, 2012), information leakage of sovereign credit rating changes prior to sovereign rating change announcements (Michaelides, Milidonis, Nishiotis, and Papakyriakou, 2014), spillover effect of sovereign credit rating changes (Gande and Parsely, 2005; Ferreira and Gamma, 2007), and the effect of ceiling policy of sovereign credit ratings on corporate decisions (Almeida, Cunha, Ferreira, and Restrepo, 2014).

Authority, 2013). Hence, the sovereign credit rating reports can serve as an ideal testing ground for us to verify if CRAs can provide valuable information for the sovereign credit market even without the access to insider information or without direct monetary compensation from their rating services.

We perform textual analysis on sovereign credit rating reports published by Moody's for more than 70 countries from 2003 to 2013 using a Naïve Bayesian algorithm. We classify every sentence in each report into two linguistic tone categories (positive and negative) and six content categories (macroeconomic, public & external finance, debt dynamics, financial sector, political & institutional, and others). We then quantify the overall positive and negative tone in each report and the positive and negative tone within each content category.

We have two main results. First, we find that the negative linguistic tone in the credit rating reports contains new default-related information. We use three sets of default-risk measures and find significant relations between these measures and the negative tone of the report. The first measure is the abnormal sovereign CDS spread change within the 3-day rating change announcement window. The second measure is the future sovereign credit rating downgrade in a one-year or two-year horizon. The third measure is a set of conventional country-level default predictors. Our results show that the negative tone is significantly related to abnormal CDS spread change and the future rating downgrade at the 5% significance level. Specifically, a one-standard deviation increase in negative tone results in a 3.1% increase in abnormal CDS spreads within the 3-day event window. This tone reaction is also economically significant as the market reaction to upgrades is only at −0.7% and to downgrades is at 2.7%. Moreover, a one-standard-deviation increase in negative tone can lead to an increase of downgrade probability by 16.1% in a one-year horizon and 13.9% in a two-year horizon. The explanatory power of the conventional default predictors for positive and negative tone has an adjusted R^2 ranging from 35% to 53%.

Second, we want to identify the most valuable information content in the rating reports. Our results reveal that the negative debt dynamics related sentences among six categories are related to most significant CDS market reaction. Specifically, a one-standard deviation increase in the negative debt-dynamics related sentences leads to a 1.6% increase in abnormal CDS spreads within the 3-day event window. More interestingly, we find a systematic decrease in the information value of negative financial risk related sentences after the onset of the Eurozone sovereign debt crisis in 2009, which indicates a loss of confidence by investors on the financial risk assessment in credit rating reports.

We conduct three robustness tests. First, we check whether the CDS market overreacts or underreacts to the tone as a validity check for the information value of the reports. We find that there are no systematic reversals or drifts in the post-announcement CDS spreads. Second, we verify that the information value of the tone is incremental to other rating actions such as credit watch and rating outlooks. Third, we decompose the tone into predicted tone and the residual tone by employing the conventional default prediction model. We find that both negative components are significantly related to the abnormal CDS spreads at the 5% significance level, suggesting that the market does not fully predict the negative contents of the rating reports. All these results confirm the robustness of our main results.

Our study makes two distinctive contributions. First, we extend the literature on sovereign credit ratings by showing that sovereign credit rating reports provide incremental information value beyond sovereign rating actions. Investors can employ sovereign credit rating reports as a source of information to assess default risk of the country. Second, our study has important policy implications for regulators and policymakers. In view of the increased volatility of sovereign credit ratings in recent years, European Securities and Markets Authority (ESMA) instituted several regulations to enhance the transparency and quality of sovereign credit ratings. For example, ESMA conducted an investigation on sovereign credit ratings issued by major rating agencies and identified various issues involved in the rating process including independence, confidentiality of rating information, timing of publication of rating actions, and resources allocated to conduct sovereign credit ratings (European Securities and Markets Authority, 2013). However, little attention has been paid to the regulation on sovereign credit rating reports so far. Our study highlights the importance of sovereign credit rating reports, a channel through which CRAs demonstrate the accountability and rigor of their systematic credit risk assessment behind sovereign rating decisions. Hence, a more careful consideration maybe needed to improve the regulation on the format and content of sovereign credit ratings to meet the demand from investors for better and more reliable information.[2]

The remainder of the paper is organized as follows. Section 2 develops our empirical hypotheses. Section 3 describes our methodology, data and key variables. Section 4 presents our two main results and section 5 presents the robustness tests. Finally, section 6 concludes.

2. HYPOTHESIS DEVELOPMENT

This section proposes our empirical hypotheses.

2.1 The Information Value of Linguistic Tone

Credit rating reports communicate opinions of creditworthiness of rated entities to investors. They contain not only rating actions but also qualitative information such as rationale that justifies rating action decisions. As an industry practice, CRAs provide credit rating action reports during credit rating action announcements and do not charge any additional fees for the production and dissemination of credit rating reports.[3] The literature has primarily focused on the information value of credit rating actions. For example, Cantor

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[2] While Regulation (EU) No 462/2013 (45) requires disclosures of key elements underlying rating decisions when publishing sovereign credit ratings. There is no specific guidance with regards to what types of quantitative and qualitative information should be included in the disclosures, unlike SEC Rule 17g-7.

[3] Appendix B provides two sample sovereign rating reports.

and Packer (1996) and Reisen and von Maltzan (1999) have found significant market reaction to sovereign credit rating changes in the sovereign bond market. With the development of the credit derivatives market, recent studies have found the significant market reaction to rating changes in sovereign CDS markets (e.g., Ismailescu and Kazemi, 2010; Kiff, Nowak and Schumacher, 2012; Afonso, Furceri and Gomes, 2012). Overall, the literature finds that sovereign credit rating actions contain new information.

Since rating rationales in credit rating reports may also contain information about CRA's assessment of default risk as a valuable supplement to discrete rating actions, we aim to examine the information value of sovereign credit rating reports. To capture qualitative information contained in credit rating reports, we rely on the prior literature that employs linguistic tone to quantify the qualitative information content in documents. These studies have employed textual analysis techniques to show that linguistic tone in news articles (Tetlock, 2007), corporate filings (Kothari, Li and Short, 2009; Li, 2010) and analyst reports (Huang, Zang and Zheng, 2014) has significant information value and market impact. The literature generally finds that linguistic tone contains valuable information for the stock market and positive (negative) tone is related to positive (negative) returns. We therefore state our first hypothesis as follows:

> ***Hypothesis 1 (The information value of tone):*** *The linguistic tone in sovereign credit rating reports contains new default-related information beyond credit rating changes.*

We employ three sets of empirical measures to proxy for the default risk of the underlying country. The first measure is the abnormal CDS spread change within the 3-day event window when the rating reports are released. The second measure is the future sovereign credit rating downgrade in a one-year and two-year horizons. The third set of measures comes from the sovereign debt literature in which several conventional default predictors are shown to be significantly related to the bond yields. These variables include global market factors, risk premiums, liquidity patterns and macroeconomic fundamentals (Longstaff, Pan, Pedersen and Singleton, 2011; Oura and Valckx, 2013). Specifically, the total debt to GDP ratio, history of recent default, currency depreciation, growth rate of foreign reserves, as well as market sentiments have been shown to be some of the most important determinants of sovereign default risk (Maltritz and Molchanov, 2013). We will test their relations with the tone in the reports.

2.2 The Information Value of Sovereign Credit Rating Reports

If **Hypothesis 1** is supported, a natural follow-up question is the relative importance of different types of information contained in the sovereign credit rating reports. In the corporate rating literature, Goh and Ederington (1993) and Chung, Frost, and Kim (2012) examine market reactions to firm-level credit rating actions conditional on specific events that trigger rating actions to provide additional insights. In assigning sovereign credit ratings, CRAs usually identify a set of rating indicators which constitute the key content of these reports as the rationales justifying the rating actions. Since the main role of CRAs is the provision of risk assessments on issued debt, they usually provide information on sovereign debt dynamics, such as principal and interest arrears, and the contingent liabilities of the government. This type of information is usually less readily available in the public domain. Together with the analyses of its repercussions on sovereign credit ratings, they constitute the value added by CRAs for investors. Moreover, CRAs also take into account other rating indicators such as macroeconomic fundamentals, public and external finances, political and intuitional risk obtained from secondary sources such as the IMF, World Bank, OECD and the general news media (Gaillard, 2013).

Given the fact that there is a large body of public information sources on sovereign macroeconomics, public and external finances, and political risk, we believe that the financial markets are likely to have reacted to these rating indicators before they trigger credit rating changes from the CRAs and the release of rating reports. On the other hand, given that the expertise of CRAs lies in their assessments on issued debt, investors are more likely to pay attention to or to react to rating rationales related to sovereign debt dynamics. Hence, we expect that the information value in debt dynamics related content in the reports is more important. Hence we state the second hypothesis as follows:

> ***Hypothesis 2 (The information content of credit rating reports):*** *The debt-related content of the credit rating reports is valuable information to the CDS markets.*

In the empirical analysis, we code all the sentences of each report into six categories of information such as macroeconomic, public & external finance, debt dynamics, financial sector, political & institutional, and other information. These content categories are based on 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). The sixth category, "others", acts as a catch-all for descriptive sentences with little information content on rating rationales. We provide the details on these categories in Table C1 of Appendix C.

Another way to validate the information content of the rating reports is to examine whether there is structural change over time. In particular, we focus on the 2009 Eurozone sovereign debt crisis because the literature has emphasized the role played by the European banking system in precipitating and exacerbating the Eurozone sovereign debt crisis (Mody and Sandri, 2011; Noeth and Sengupta, 2012; Zaharia and Zaharia, 2013). Cheap funding in the U.S. money markets allowed global European banks to expand their balance sheets and significantly increase leverage. The introduction of the Euro and its appreciation relative to other major currencies subsequently led to a reduction in risk premia for these banks. Credit booms and increased risk-taking followed, which eventually set in motion a cycle of declining prices, non-performing assets and bank deleveraging. The hypothesis of the three interlocking crises proposed by Shambaugh (2012) explains how the European banking crisis led to an economic recession and subsequently a sovereign debt crisis. CRAs were criticized after the banking collapse in 2008 for their failure in providing accurate risk assessments of complex financial products (Ryan, 2012). After the onset of the Eurozone crisis, many concerns were raised by regulators and investors to question the independence of CRAs and the equality of their sovereign risk assessments (e.g., Dodd-Frank Wall Street Reform and Consumer Protection Act, 2010; European Securities and Markets Authority, 2013). In light of this, we verify whether the information value of sovereign credit rating reports has changed over time due to the heightened criticism and scrutiny by investors and regulators. In this way, we can further validate **Hypothesis 2** in the light of possible changing attitude by the public toward CRAs before and after the Euro crisis.

3. METHODOLOGY, DATA AND KEY VARIABLES

In this section, we describe the use of our Naïve Bayesian machine learning algorithm to measure tone and content, our dataset, key variables and present summary statistics.

3.1 Measurement of Linguistic Tone and Report Content

We measure the tone and content of credit rating reports using the Naïve Bayesian machine learning algorithm. It is a textual analysis technique which functions by classifying sentences in a text into specific categories out of a set of pre-defined categories. A more detailed description of our algorithm is provided in Appendix C. In this study, we classify 10,278 sentences in 323 reports along the tone and content dimensions. The tone reflects the qualitative information in credit rating reports and comprises three categories: positive (POS), negative (NEG), and neutral. The positive (negative) tone is the percentage of positive (negative) sentences in the report. The neutral tone is the percentage of sentences that are neither positive nor negative. The net tone is defined as the positive tone minus the negative tone. The content reflects the rationales used to justify rating actions in the reports and comprises six categories mentioned above. Each content category has a score, which is defined as the percentage of sentences classified in a particular content category. An analysis of our text classification results is presented in Appendix C. Overall, 30.3% of sentences are classified as positive and 50.9% as negative. Macroeconomic, public & external finance and debt dynamics constitute 35.7%, 11.4% and 18.1% of sentences respectively.

Figure 1 presents the mean net tone scores by report type. As expected, positive rating actions have mean positive net tone, while negative rating actions have mean negative net tone. An analysis of the variation of tone in Moody's reports over the last decade, as presented in Figure 2, indicates an increasing use of more negative tone, particularly from 2009 onwards (corresponding to the onset of the Eurozone debt crisis).

[Insert Figure 1 and 2 about here]

We also use our algorithm to compute the tone within each content category, CONTENT_POS and CONTENT_NEG, where CONTENT represents five categories of information such as macroeconomic (MACRO), public & external finance (PEF), debt dynamics (DEBT), financial sector (FIN) or political & institutional (POL).[4] For each content category, we also calculate the residual positive and negative tone (POS_RES and NEG_RES) in the report after removing the tone related to that specific content category. These are computed by (POS – CONTENT_POS) and (NEG – CONTENT_NEG). These separations allow us to compare the information value of each content category with the combination of other categories in the rating reports.

3.2 Definitions of Key Variables

Cumulative Abnormal Sovereign CDS Spread Percentage Changes

[4] Here, we do not consider the sixth "other" category as it captures the remaining sentences that are not classified into the specific five information categories.

Our key dependent variable is the cumulative abnormal CDS spread percentage change (CDS), summed over the 3-day event window [-1, 1]. A key advantage of using sovereign CDS spreads over sovereign debt spreads is that it 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 bond, and illiquidity effects in debt prices (Ang and Longstaff, 2013). Daily CDS mid-spread quotes of the 70 countries in our sample from 2003 to 2013 were obtained from Thomson Reuters DataStream. 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 where U.S. dollar-denominated contracts were unavailable.

We use a market model to calculate the cumulative abnormal CDS spread percentage changes. There is currently no established market model in the literature to calculate CDS spread changes for event studies. As such, our market model is adapted from Hull, Predescu and White (2004), Norden and Weber (2004) and Ismailescu and Kazemi (2010). To account 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), we use the abnormal CDS spread percentage change. For each event country, we construct two CDS market indices that are equally-weighted cross-sectional averages of the CDS spreads of all non-event countries in our sample for a particular rating class. The two CDS market indices correspond to two rating classes: investment- and speculative-grade. The daily abnormal CDS spread percentage change is the CDS spread percentage change of the event country less the CDS spread percentage change of the market index corresponding to the rating class 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 of all non-event countries of the same rating class excluding event country k at time t. The cumulative abnormal CDS spread percentage change over the 3-day event window, CDS(-1,1), is then computed as the sum of the daily abnormal CDS spread percentage changes. 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).

Other Key Variables

To study the information content of tone, we construct two dummy variables that represent future rating downgrades over one- and two-year horizons, namely 1-YR FUTURE DOWNGRADE and 2-YR FUTURE DOWNGRADE.

To investigate the fundamental determinants of tone in credit rating reports, we include several key explanatory variables from the literature on sovereign default risk (e.g., Oura and Valckx, 2013; Maltritz and Molchanov, 2013). These include the variables INITIAL_RATING, RECENT_DEFAULT, GDP_GROWTH, DEBT_GDP, FRES_GDP, FRES_GROWTH, FX_GROWTH, TRADEBAL_GDP, SP500, FISCAL_FREEDOM, MONETARY_FREEDOM, FINANCIAL_FREEDOM and HIGH_STRESS. For definitions of these country-level default predictors, please refer to Table A1 in Appendix A.

Control Variables

Our key control variables for credit rating actions include DOWN, POS_WATCH, NEG_WATCH, POS_OUTLOOK and NEG_OUTLOOK. Following Goh and Ederington (1993) and Avramov, Chordia, Jostova and Philipov (2009), we include INITIAL_STATUS, RISING_STAR and FALLEN_ANGEL. Sovereign default risk, as reflected by sovereign CDS spreads, is driven macroeconomic and global market factors, risk premiums and liquidity patterns. Following Longstaff, Pan, Pedersen and Singleton (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 variables LOCAL_MKT, FX_RATE, US_MKT, TREASURY_MKT, VOLRISK_PREM and ADS_INDEX. 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. These variables are defined in Table A1 in Appendix A.

3.3 Summary Statistics

Table 1 Panel A describes our sample selection process. We start from 405 credit rating reports downloaded from Moody's Research & Ratings database from 2003 to 2013. We remove 82 reports which do not have corresponding sovereign CDS data in DataStream. Of the remaining 323 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. 80 reports (48.2%) are for upgrades and 86 (51.8%) are for downgrades.

[Insert Table 1 here]

Table 1 Panel B presents the summary statistics of our key variables. The mean cumulative abnormal CDS spread percentage change CDS(-1,1) is 0.55%, consistent with the majority of credit rating actions being downgrades (51.8%). The proportions of downgrades within one- and two-year horizons are 21.08% and 24.10% respectively. The mean positive tone and negative tone are 0.3621 and 0.3984 respectively. Table 1 Panel C presents the correlation matrix for our key variables. We find that, as expected, positive tone is negatively correlated with downgrades and fallen angels. Negative tone is positively correlated with downgrades but negatively correlated with rising stars.

4. EMPIRICAL FINDINGS

4.1 The Information Value of Tone

To test **Hypothesis 1** on the information value of tone, we employ three sets of default risk measures, such as abnormal CDS spread change, the future rating downgrade, and a set of default risk predictors at the country level. Table 2 reports the results when we employ the cumulative abnormal sovereign CDS spread percentage change over the 3-day event window surrounding the announcement date, CDS(-1,1) as the dependent variable.

[Insert Table 2 here]

First two models in Table 2 provide the base case where CDS market reacts strongly towards downgrades. Model 1 shows that the abnormal CDS spread change in response to downgrades (DOWN) is significant at 4.6%, while the response to upgrades is significant at −1.8%. This result is consistent with the literature, which finds that downgrades induce greater CDS market reactions (Norden and Weber, 2004; Afonso, Furceri and Gomes, 2012). Model 2 includes the control variables INITIAL_STATUS, RISING_STAR, FALLEN_ANGEL, LOCAL_MKT, FX_RATE, US_MKT, TREASURY_MKT, VOLRISK_PREM and ADS_INDEX. The effect of downgrades remains significant at 2.7%, but the effect of upgrades diminishes considerably to -0.7% and is no longer significant. Both RISING_STAR and FALLEN_ANGEL are significant with the expected signs, indicating that upgrades (downgrades) through the investment-speculative-grade boundary lead to significant decreases (increases) in CDS spreads.

We find supporting evidence for **Hypothesis 1** after we include positive tone (POS) and negative tone (NEG) in Model 3. Model 3 includes POS, NEG and DOWN (where neutral tone is the base case). Model 4 further includes the control variables. We find that NEG is positively and significantly related to abnormal CDS spread changes beyond credit rating changes at the 5% level in all these models. We also find that the information value of negative tone is significantly greater than that of positive tone. This asymmetric information value of tone can be attributed to the difference in importance that investors assign to positive versus negative tone. As downgrade is a more severe event than upgrade, CRAs are more cautious about providing additional information to justify their downgrade decisions (e.g., Beaver et al., 2006; and Jorion and Zhang, 2007). As such, tones in downgrade reports are expected to be more informative than upgrade reports. Moreover, managers tend to withhold bad news but release good news early (e.g., Ederington and Goh, 1998; Kothari, Shu, and Wysocki, 2009). Hence, negative tone contains more information value than positive tone, resulting in the observed asymmetric effect of tone. Model 4 shows that a one-standard deviation increase in negative tone results in a 3.1% increase in abnormal CDS spreads within the 3-day event window surrounding rating changes. This tone reaction is also economically significant, especially in comparison to the reactions attributed purely to upgrades (-0.7%) and downgrades (2.7%). Among the control variables, VOLRISK_PREM is significant at the 5% level and has a negative coefficient. This is also consistent with Longstaff, Pan, Pedersen and Singleton (2011), who find that the time-varying volatility risk premium is one of the most important components of sovereign CDS spreads.

Table 3 reports the results when we employ future credit rating changes as the second set of default risk measures. Specifically, we regress the dummy variables, 1-YR FUTURE DOWNGRADE and 2-YR FUTURE DOWNGRADE on tone.

[Insert Table 3 here]

We find that negative tone can predict future rating downgrades. Model 1 and Model 3 in Table 3 set the benchmark case without tone and show that there is rating momentum over one- and two-year horizons, wherein current downgrades predict future downgrades. Model 2 and Model 4 include positive and negative tone (POS and NEG). The coefficients of negative tone are 0.6289 and 0.5443 for one- and two-year horizons, and are significant at the 1% and 5% levels respectively. A one-standard deviation increase in negative tone translates to an increase in the probability of future downgrades by 16.1% and 13.9% within one- and two-year horizons respectively. The significant relation between tone and future downgrades indicates that tone contains default related information.

In the final test, we regress the tone on a set of lagged variables that can explain sovereign default risk in the literature (Oura and Valckx, 2013; Maltritz and Molchanov, 2013). These variables include RECENT_DEFAULT, GDP_GROWTH, DEBT_GDP, FRES_GDP, FRES_GROWTH, FX_GROWTH, TRADEBAL_GDP, SP500, FISCAL_FREEDOM, MONETARY_FREEDOM, FINANCIAL_FREEDOM and HIGH_STRESS. They are measured in either last month or last quarter depending on the data availability before the report's releasing date. We also include one dummy variable that capture the investment-grade status of the sovereign rating, INITIAL_STATUS, and the numeric credit rating of the sovereign, INITIAL_RATING. Table 4 reports the regression results with robust standard errors.

[Insert Table 4 here]

Our results show that the conventional determinants of sovereign default risk play a significant role in explaining positive and negative tone in credit rating reports. In subpanels (1) and (2) in Table 4, we use positive and negative tone as the dependent variables respectively. Model 1 employs the sample of credit rating changes. Model 2 employs the sample of credit rating changes and credit watchlist actions. Model 3 employs the sample of rating changes, watchlist, and rating outlook actions.

All the six models in Table 4 show that the coefficients of INITIAL_RATING, GDP_GROWTH, DEBT_GDP, FRES_GDP, TRADEBAL_GDP and HIGH_STRESS are highly significantly related to positive and negative tone (most at the 1% or 5% level), with the expected signs. Higher initial ratings, higher GDP growth, lower debt to GDP ratio, higher ratio of foreign reserves to GDP, higher ratio of trade balance to GDP, and a lower probability of the VIX index being in a high volatility state are significantly related to more positive tone, and vice versa for negative tone. The significance of most coefficients (with the expected signs) in our regression model supports **Hypothesis 1** that tone is significantly related to sovereign default risk. This finding also offers an explanation for the significant impact of tone on sovereign CDS spreads, which are important indicators of sovereign default risk (Longstaff, Pan, Pedersen and Singleton, 2011).

Overall, our results by employing three sets of default risk measures support **Hypothesis 1** that tone in sovereign credit rating reports contains new default-related information beyond credit rating changes.

4.2 The Information Content of Credit Rating Reports

In this section, we test **Hypothesis 2** by verifying that the most important information content of credit rating reports is related to sovereign debt among other information contents.

First, we regress the cumulative abnormal CDS spread percentage change over the 3-day event window surrounding the rating change announcement date, CDS(-1,1), on the positive and negative tone within each content category as well as a set of control variables. Table 5 reports the regression results with robust standard errors. Subpanels (1) to (5) present the results for the five content categories: macroeconomic, public & external finance, debt dynamics, financial sector, and political & institutional.

[Insert Table 5 here]

We find strong support for **Hypothesis 2** that the market places greater importance on negative tone related to debt dynamics content in sovereign credit rating reports above and beyond other content categories. We run separate regressions for each content category, which represent the categories of rating rationales used to justify rating actions in credit rating reports (CONTENT_POS and CONTENT_NEG). In the same regression, we also include the residual positive and negative tone related to the remaining information contents (POS_RES and NEG_RES) to assess the relative importance of one specific category with the rest categories in combination. Subpanel (3) shows that negative tone related to debt dynamics content is statistically significant, whereas subpanels (1), (2), (4) and (5) show that negative residual tone (which are related to macroeconomic, public & external finance, financial sector, and political & institutional information categories) are not statistically significant. Specifically, CONTENT_NEG that is related to debt dynamics is highly significant at the 1% and 5% levels in Model 5 and Model 6 of subpanel (3), while NEG_RES is not significant. The opposite is observed for the models in subpanels (1), (2), (4) and (5), where CONTENT_NEG is not significant while NEG_RES is significant. The exception is Model 1, where CONTENT_NEG related to macroeconomic category is significant at the 10% level. However, it is no longer significant in Model 2 after including control variables. The CDS market impact of negative tone related to debt dynamics content in sovereign credit rating reports is economically significant. From Model 6 in subpanel (3), we find that a one-standard deviation increase in negative tone related to debt dynamics content results in a 1.9% increase in abnormal sovereign CDS spreads. This accounts for approximately 62% of the CDS market reaction to negative tone as a whole (3.1%). The significance of the negative tone in other categories in these subpanels indicates that the impact of negative tone on sovereign CDS spreads is mainly related to debt dynamics rather than other categories.

To further validate **Hypothesis 2**, we repeat the above regressions by introducing a time dummy variable. POST2009 is a dummy variable that equals 1 if the year of the current rating action is after 2009 (i.e. 2010 and beyond), and 0 otherwise. Our choice of this time dummy is motivated by the recent Eurozone sovereign debt crisis and the first instances of the three major CRAs downgrading Greek government and bank debt in late 2009. Table 6 reports the regression results with robust standard errors.

[Insert Table 6 here]

We find that negative tone related to financial sector content in sovereign credit rating reports has become less informative over time, particularly after the Eurozone debt crisis. Models 1, 3, 5, 7 and 9 report the regression results on the downgrade dummy variable (DOWN), positive and negative tone related to each information category (CONTENT_POS and CONTENT_NEG), the residual tone related to the remaining information categories (POS_RES and NEG_RES), POST2009, and its interactions with POS_RES, NEG_RES, CONTENT_POS and CONTENT_NEG. Models 2, 4, 6, 8 and 10 further include control variables. Notably, in subpanel (4) Model 7 and Model 8, the coefficients of CONTENT_NEG (related to financial sector content) are significant at the 5% level and have the expected positive signs, while the interaction terms of POST2009 with CONTENT_NEG (POST2009×CONTENT_NEG) are also significant at the 5% level and have negative coefficients. This indicates a systematic decrease in the information value of negative tone related to financial sector content after 2009. From our results in Model 8, prior to 2009, a one-standard deviation increase in negative tone related to financial sector content results in an increase in sovereign CDS spreads by 4.2%. This is reduced to 0.2% after 2009, a tremendous decrease of approximately 95%. The fact that 55.4% of our sample contains rating changes that took place after 2009 explains the insignificance of the coefficient of CONTENT_NEG related to financial sector content that was observed in our earlier testing of **Hypothesis 2** in Table 5. These findings suggest increased suspicion of investors on CRAs' assessment on financial sector-related rating rationales in the rating reports.

Overall, our results support **Hypothesis 2** that the debt dynamics related content of sovereign credit rating reports is most valuable to investors. Moreover, we also find that the information value of certain content categories in sovereign credit rating reports can change over time.

5. ROBUSTNESS TESTS

In this section, we perform three sets of robustness tests. First, we verify whether the CDS market reaction toward tone has any drifts or reversals after the announcement. This test can further validate the information value of the tone. Second, we also include other rating actions in the base model by verifying that the tone still contains novel information beyond rating guidance provided such as watchlist or outlook. Lastly, we verify whether investors can fully anticipate the information content of the rating reports, given that the literature finds early leakage of sovereign rating actions before the announcement (e.g., Michaelides, Milidonis, Nishiotis, and Papakyriakou, 2014).

5.1. Post-announcement Drift?

We investigate post-announcement long-run CDS market reactions 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]. Due to the relatively small number of observations in each portfolio, the results of 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 7 reports our results.

[Insert Table 7 here]

We find little evidence that post-announcement long-run CDS spreads are significantly related to tone from Panel A to Panel B in Table 7. We find that only the portfolio 1 with the lowest positive tone has positive drift in the CDS after 20 days, the other drifts are mostly insignificant. Hence, there is no systematic reversals or drifts after the rating announcements.

We illustrate the CDS changes during the rating changes in Figure 3, which plots the mean daily cumulative abnormal CDS spread changes of all event countries across the window [−90,90] for credit rating changes announced by Moody's. The figure clearly shows that CDS starts to drift up or down before the actual rating announcements, consistent with Michaelides, Milidonis, Nishiotis, and Papakyriakou (2014). More importantly, we do not see much of further drifts after the announcements, suggesting that the market is efficient in processing the tone.

[Insert Figure 3 about here]

5.2 Tone and Other Rating Actions

Our second robustness test focuses on the information value of tone in the presence of other contemporaneous credit rating actions such as watchlist and outlook actions. CRAs issue credit watchlist and outlook actions in addition to rating changes. Watchlist and outlook actions may pre-empt rating changes, or may accompany rating changes as a signal of the direction of possible future rating changes (Bannier and Hirsch, 2010; Chung, Frost and Kim, 2012; Alsakka and Gwilym, 2012). If watchlist and outlook actions provide similar information to tone, we expect the significance of tone as an explanatory variable to diminish. Alternatively, if tone provides different information and is used by CRAs to augment watchlist and outlook actions, we expect tone to remain as a significant explanatory variable. Table 8 presents our results.

[Insert Table 8 here]

Table 8 shows that tone is robust even after taking into account watchlist and outlook actions. Model 1 includes dummy variables for various rating actions, such as rating upgrade and downgrade (UP and DOWN), positive and negative watch (POS_WATCH and NEG_WATCH), and positive rating outlook (POS_OUTLOOK).[5] Model 2 includes control variables. We find that among these rating actions, only rating upgrade is significantly associated with abnormal CDS spread changes. In Model 3 where we include positive and negative tone and control for rating change actions, the results indicate that the coefficients of negative tone remain positive and significant at 10% level, suggesting that the information value of tone is incremental to that of rating change actions. Similarly, in Model 4 and Model 5, we find that the coefficients of negative tone remain positive and significant at the 5% and 10% level when we control for credit watch and rating outlook, respectively. We include all types of credit rating actions in Model 6 and our analysis indicates that the coefficient on negative tone continues to be positive and statistically significant at the 5% level. Overall, our results show that tone provides information value about default risk incremental to various rating actions.

We also verify whether tone can predict future rating downgrades in the presence of other rating actions. Table 9 presents our results. Again, we find that negative tone remains a significant predictor of future downgrades even after taking into account various rating actions, which indicates that negative tone contains incremental information on default risk beyond negative watch actions. Our main results remain robust with respect to various rating actions.

[5] We use negative rating outlook (NEG_OUTLOOK) as base in the regression.

[Insert Table 9 here]

5.3 The Predictability of Tone

Given that the literature has shown that the CDS market can anticipate rating changes (Hull, Predescu and White, 2004; Ismailescu and Kazemi, 2010; Michaelides, Milidonis, Nishiotis, and Papakyriakou, 2014), it is possible that market participants may anticipate the information in forthcoming credit rating reports. This prompts us to examine the information role of anticipated and surprise tone in credit rating reports.

To construct the predicted and residual tone measures, we first use the deterministic model developed in Table 4 using lagged default predictors. This yields a model-predicted positive or negative tone (POS_P and NEG_P) for each credit rating report that can be used to estimate the residual positive and negative tone (POS_S and NEG_S) by subtracting the POS_P and NEG_P from the initial level of positive and negative tone in each report (POS and NEG).

We regress the cumulative abnormal sovereign CDS spread percentage change over the 3-day event window surrounding the announcement date, CDS(-1,1), on the predicted and residual components of positive and negative tone in our credit rating reports as well as a set of control variables. Table 10 subpanel (1) reports the regression results with robust standard errors.

[Insert Table 10 here]

Interestingly, we find that both the predicted and residual tone have information value. Model 1 reports the regression results on the downgrade dummy variable (DOWN), the positive and negative predicted tone (POS_P and NEG_P), and the positive and negative residual tone (POS_S and NEG_S). The coefficients of NEG_P and NEG_S are both significant at the 5% level and have the expected positive signs. Model 2 further includes control variables. NEG_P and NEG_S remain significant at the 5% level. In both models, POS_P and POS_S are insignificant. Our results are consistent with that in **Hypothesis 1**, where we find that positive tone contains less information value than negative tone.

These findings indicate that investors are unable to fully anticipate the degree of positivity or negativity of forthcoming credit rating reports. Instead, they react when credit rating reports confirm their expectations, as indicated by the significant coefficients of negative anticipated tone (NEG_P). In addition, they react to information surprises, as indicated by the significant coefficients of negative surprise tone (NEG_S).

In Subpanel (2) in Table 10, we also include in our regression the lagged sovereign default risk variables from our deterministic Model 1 in Table 10. If tone does indeed have information value beyond what the market can predict, we would expect tone to remain significant even after including the lagged sovereign default risk variables and the lagged CDS spread for the prior month in our regressions. On the other hand, if the information contained in tone is entirely driven by the lagged sovereign default risk variables (in other words, CRAs do not provide any new information), or this information is already captured in the lagged CDS spread for the prior month, we would expect tone to be insignificant. Model 3 to Model 5 report the regression results with robust standard errors (from Model 3 to Model 5). We find that the coefficients on negative tone are consistently significant from Model 3 to Model 5, which verify **Hypothesis 1**. Overall, our robustness tests provide consistent results as before. We find important information value of tone and the sovereign credit rating reports in CDS markets.

6. CONCLUSION

In this study, we investigate the information value of credit rating reports issued by Moody's. We find that negative tone is significantly related to the 3-day abnormal sovereign

CDS spread change at the time of rating announcements beyond rating actions and negative tone has greater information value than positive tone. Negative tone can predict future rating downgrades over one- and two-year horizons and is significantly related to macroeconomics predictors. Taken together, our results suggest that tone contains default-related information.

Moreover, we confirm that the market places greater importance on negative debt dynamics content in the rating reports above and beyond other content categories. Interestingly, the information value of financial sector content has declined after the onset of the Eurozone sovereign debt crisis in 2009, plausibly due to the drop of investors' trust in CRAs.

Our study sheds lights on the information value of sovereign credit rating reports in sovereign CDS market for the first time in the literature. Sovereign credit ratings differ from corporate credit ratings in several dimensions and CRAs may not be properly incentivized to maintain the quality of sovereign credit ratings as well as corporate credit ratings (Fulghieri, Strobl, and Xia, 2013). Overall, our findings reveal an important information role provided by CRAs in assessing sovereign default risk and in providing useful information in the rating reports for investors.

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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
CDS(1,10)	166	-0.0097	-0.0071	0.1225	-0.6023	0.2812
CDS(1,20)	166	-0.0042	0.0015	0.1457	-0.6092	0.2971
CDS(1,30)	166	0.0225	0.0168	0.1894	-0.6639	0.5424
CDS(1,45)	166	0.0269	0.0136	0.2658	-0.9441	1.3084
CDS(1,60)	166	0.0119	0.0090	0.3266	-1.4057	1.2936
CDS(1,90)	166	0.0682	0.0270	0.4979	-1.4925	2.0797
1-YR FUTURE DOWNGRADE	166	0.2108	0.0000	0.4091	0.0000	1.0000
2-YR FUTURE DOWNGRADE	166	0.2410	0.0000	0.4290	0.0000	1.0000
Key Independent Variables						
UP	166	0.4819	0.0000	0.5012	0.0000	1.0000
POS	166	0.3621	0.3529	0.1992	0.0000	0.8571
NEG	166	0.3984	0.4000	0.2553	0.0000	0.9375
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
IG_SPREAD	166	0.0037	0.0035	0.0477	-0.1914	0.2087
HY_SPREAD	166	0.0014	0.0005	0.0821	-0.1820	0.2330
EQUITY_PREM	166	0.0219	0.0316	0.2618	-1.2874	1.1665
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
HIGH_STRESS	166	0.1282	0.0013	0.3035	0.0000	1.0000
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	0.0316	0.0332	0.0460	-0.0776	0.2617
DEBT_GDP	166	0.6140	0.5327	0.3936	0.0492	1.9332
FRES_GDP	166	0.1153	0.0750	0.1287	0.0012	0.9076
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
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
POS_S	166	0.1274	0.0000	0.1791	0.0000	0.8192
NEG_S	166	0.1285	0.0134	0.1727	0.0000	0.8286
Other Variables						
POS_WATCH	234	0.1624	0.0000	0.3696	0.0000	1.0000
NEG_WATCH	234	0.1752	0.0000	0.3810	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

Panel C: Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	UP	-													
		-													
(2)	POS	0.86***	-												
		(0.00)	-												
(3)	INITIAL_STATUS	0.18*	0.19*	-											
		(0.02)	*(0.02)*	-											
(4)	RISING_STAR	0.28***	0.33***	0.30***	-										
		(0.00)	*(0.00)*	*(0.00)*	-										
(5)	FALLEN_ANGEL	-0.22**	-0.21**	-0.20*	-0.06	-									
		(0.00)	*(0.01)*	*(0.01)*	*(0.44)*	-									
(6)	LOCAL_MKT	0.03	0.03	-0.03	0.05	-0.04	-								
		(0.69)	*(0.70)*	*(0.66)*	*(0.53)*	*(0.63)*	-								
(7)	FX_RATE	-0.01	-0.02	-0.03	0.03	-0.05	0.63***	-							
		(0.91)	*(0.83)*	*(0.72)*	*(0.73)*	*(0.51)*	*(0.00)*	-							
(8)	US_MKT	0.08	0.06	0.08	0.04	-0.01	0.28***	0.15	-						
		(0.31)	*(0.42)*	*(0.30)*	*(0.60)*	*(0.94)*	*(0.00)*	*(0.06)*	-						
(9)	TREASURY_MKT	-0.10	-0.06	0.06	0.08	-0.00	0.13	0.06	0.20*	-					
		(0.20)	*(0.47)*	*(0.42)*	*(0.32)*	*(0.99)*	*(0.09)*	*(0.42)*	*(0.01)*	-					
(10)	IG_SPREAD	-0.07	-0.07	-0.20**	0.01	0.06	-0.05	-0.13	0.09	-0.01	-				
		(0.37)	*(0.38)*	*(0.01)*	*(0.85)*	*(0.42)*	*(0.55)*	*(0.11)*	*(0.27)*	*(0.85)*	-				
(11)	HY_SPREAD	-0.03	0.01	-0.07	-0.01	0.02	-0.20*	-0.12	-0.35***	-0.11	-0.00	-			
		(0.74)	*(0.91)*	*(0.34)*	*(0.87)*	*(0.76)*	*(0.01)*	*(0.11)*	*(0.00)*	*(0.17)*	*(0.96)*	-			
(12)	EQUITY_PREM	-0.06	-0.07	-0.01	0.01	0.06	0.30***	0.07	0.75***	0.29***	0.19*	-0.33***	-		
		(0.41)	*(0.34)*	*(0.89)*	*(0.91)*	*(0.46)*	*(0.00)*	*(0.35)*	*(0.00)*	*(0.00)*	*(0.01)*	*(0.00)*	-		
(13)	VOLRISK_PREM	0.09	0.07	0.05	0.09	-0.01	-0.20*	-0.16*	-0.08	-0.06	0.04	0.07	-0.14	-	
		(0.26)	*(0.36)*	*(0.51)*	*(0.25)*	*(0.87)*	*(0.01)*	*(0.04)*	*(0.33)*	*(0.42)*	*(0.62)*	*(0.36)*	*(0.08)*	-	
(14)	ADS_INDEX	0.06	0.05	-0.04	-0.06	0.07	-0.04	-0.07	-0.05	-0.00	-0.16*	-0.03	-0.10	-0.05	-
		(0.47)	*(0.53)*	*(0.65)*	*(0.45)*	*(0.40)*	*(0.62)*	*(0.36)*	*(0.52)*	*(0.98)*	*(0.04)*	*(0.73)*	*(0.21)*	*(0.54)*	-
(15)	HIGH_STRESS	-0.21**	-0.16*	-0.09	-0.07	-0.08	0.00	0.20*	-0.18*	0.08	0.11	0.11	-0.00	-0.17*	-0.13
		(0.01)	*(0.04)*	*(0.23)*	*(0.35)*	*(0.30)*	*(0.99)*	*(0.01)*	*(0.02)*	*(0.32)*	*(0.17)*	*(0.14)*	*(0.95)*	*(0.03)*	*(0.09)*

Table 2. The Information Value of Tone during Credit Rating Changes

This table presents the information value of tone during credit rating changes announced by Moody's from 2003 to 2013. 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 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
DOWN	0.0462***	0.0274***	0.0075	-0.0027
	(4.39)	(2.77)	(0.38)	(-0.14)
POS			0.0249	0.0520
			(0.56)	(1.12)
NEG			0.1059**	0.1005**
			(2.41)	(2.25)
INITIAL_STATUS		-0.0095		-0.0138
		(-0.93)		(-1.29)
RISING_STAR		-0.0378**		-0.0396**
		(-2.31)		(-2.35)
FALLEN_ANGEL		0.0946***		0.0855**
		(2.80)		(2.49)
LOCAL_MKT		-0.4232*		-0.4097*
		(-1.80)		(-1.83)
FX_RATE		-0.0985		-0.0185
		(-0.47)		(-0.08)
US_MKT		-0.2333		-0.2994
		(-0.87)		(-1.13)
TREASURY_MKT		-0.9805		-0.8474
		(-0.15)		(-0.14)
VOLRISK_PREM		-0.2800**		-0.2692**
		(-2.27)		(-2.15)
ADS_INDEX		0.0129		0.0389
		(0.09)		(0.27)
INTERCEPT	-0.0184**	-0.0070	-0.0496*	-0.0495
	(-2.58)	(-0.68)	(-1.69)	(-1.59)
N	166	166	166	166
Adj. R^2	0.10	0.29	0.13	0.31

Table 3. The Information Value of Tone in Predicting Future Rating Actions

This table presents the information value of tone in Moody's credit rating reports in predicting future rating changes from 2003 to 2013. Subpanel (1) presents the results for future rating downgrades within 1 year, while subpanel (2) presents the results for future rating downgrades within 2 years. The dependent variables are 1-YR FUTURE DOWNGRADE and 2-YR FUTURE DOWNGRADE. 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: Future Rating Downgrade			
	(1) Within 1 Year		(2) Within 2 Years	
Independent Variables	Model 1	Model 2	Model 3	Model 4
DOWN	0.4164***	0.1409	0.4685***	0.2274*
	(7.42)	(1.17)	(8.21)	(1.78)
POS		0.0045		-0.0043
		(0.02)		(-0.02)
NEG		0.6289***		0.5443**
		(2.68)		(2.24)
INITIAL_STATUS	-0.1039*	-0.1328**	-0.0909	-0.1159*
	(-1.76)	(-2.21)	(-1.50)	(-1.87)
RISING_STAR	0.0572*	0.0714*	0.0501	0.0630*
	(1.72)	(1.90)	(1.48)	(1.66)
FALLEN_ANGEL	-0.2130	-0.2794*	-0.1343	-0.1919
	(-1.27)	(-1.78)	(-0.73)	(-1.07)
INTERCEPT	0.0467*	-0.0480	0.0408	-0.0368
	(1.72)	(-0.39)	(1.48)	(-0.29)
N	166	166	166	166
Adj. R^2	0.27	0.30	0.31	0.33

Table 4. The Relation between Tone and Default Risk Predictors

This table presents the fundamental determinants of tone in Moody's credit rating reports, including watchlist and outlook actions, from 2003 to 2013. Subpanels (1) and (2) present the results of regressions using positive and negative tone scores as the dependent variables. 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: Positive Tone			Dependent Variable: Negative Tone		
	(1) Positive Tone Score			(2) Negative Tone Score		
Independent Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	rating	watchlist	outlook	rating	watchlist	outlook
INITIAL_STATUS	0.0759	0.0729*	0.0625*	-0.0649	-0.0509	-0.0508
	(1.57)	(1.76)	(1.66)	(-1.14)	(-1.14)	(-1.30)
INITIAL_RATING	-0.0119**	-0.0088*	-0.0086*	0.0158**	0.0166***	0.0113**
	(-2.03)	(-1.70)	(-1.87)	(2.03)	(2.62)	(2.15)
RECENT_DEFAULT	-0.1301**	-0.1149**	-0.1217**	0.0773	0.0898	0.0765
	(-2.43)	(-2.21)	(-2.46)	(1.24)	(1.49)	(1.35)
GDP_GROWTH	0.7487**	0.5263*	0.7898***	-1.4403***	-1.2283***	-1.2859***
	(2.25)	(1.78)	(2.78)	(-3.43)	(-3.46)	(-3.93)
DEBT_GDP	-0.1713***	-0.1575***	-0.1401***	0.1987***	0.2278***	0.2163***
	(-4.02)	(-4.61)	(-4.53)	(3.60)	(5.33)	(6.10)
FRES_GDP	0.4504***	0.3816***	0.3207***	-0.8509***	-0.8286***	-0.6977***
	(5.07)	(5.26)	(4.76)	(-6.38)	(-8.27)	(-7.69)
FRES_GROWTH	0.0305	0.0316*	0.0254	-0.0792***	-0.0649***	-0.0532***
	(1.46)	(1.74)	(1.40)	(-2.95)	(-3.07)	(-2.73)
FX_GROWTH	0.0098	-0.2502*	-0.2676**	-0.0672	0.1757	0.1094
	(0.06)	(-1.74)	(-2.01)	(-0.34)	(1.04)	(0.72)
TRADEBAL_GDP	0.2728***	0.2464***	0.2109***	-0.3501***	-0.3097***	-0.2217**
	(3.05)	(3.29)	(2.85)	(-2.83)	(-3.03)	(-2.47)
SP500	-0.4062	-0.3402	-0.2808	0.3402	0.3145	0.2821
	(-1.22)	(-1.32)	(-1.24)	(0.92)	(1.04)	(1.12)
FISCAL_FREEDOM	-0.0022*	-0.0021*	-0.0023*	0.0029*	0.0034**	0.0021
	(-1.66)	(-1.87)	(-1.90)	(1.69)	(2.39)	(1.61)
MONETARY_FREEDOM	0.0022	0.0019	0.0024	-0.0036	-0.0043*	-0.0052***
	(1.10)	(1.04)	(1.39)	(-1.35)	(-1.89)	(-2.68)
FINANCIAL_FREEDOM	-0.0010	-0.0023***	-0.0017**	-0.0001	0.0008	0.0011
	(-1.03)	(-2.71)	(-2.21)	(-0.06)	(0.73)	(1.18)
HIGH_STRESS	-0.0904*	-0.1009**	-0.0999***	0.0984*	0.1186***	0.1275***
	(-1.95)	(-2.56)	(-2.68)	(1.87)	(2.77)	(3.31)
INTERCEPT	0.6057***	0.6434***	0.5930***	0.2748	0.1773	0.3898*
	(3.08)	(3.65)	(3.29)	(0.96)	(0.77)	(1.96)
N	166	234	323	166	234	323
Adj. R^2	0.46	0.44	0.35	0.50	0.53	0.45

Table 5. The Information Value of Credit Rating Reports

This table presents the information value of tone conditional on content categories in credit rating reports during credit rating changes announced by Moody's from 2003 to 2013. Subpanels (1) to (5) present the results for five content categories: Macroeconomic, Public & External Finance, Debt Dynamics, Financial Sector and Political & Institutional. The positive and negative tone related to each of these specific content categories are represented by CONTENT_POS and CONTENT_NEG in each subpanel. POS_RES and NEG_RES are the residual positive and negative tone related to other contents. 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 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)									
	(1) Macroeconomic		(2) Public & Ext Finance		(3) Debt Dynamics		(4) Financial Sector		(5) Political & Institutional	
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
DOWN	0.0077	0.0005	0.0085	0.0012	0.0134	0.0027	0.0078	-0.0000	0.0054	0.0004
	(0.38)	(0.02)	(0.42)	(0.06)	(0.70)	(0.13)	(0.39)	(-0.00)	(0.28)	(0.02)
POS_RES	0.0320	0.0754	0.0439	0.0595	0.0258	0.0466	0.0209	0.0466	0.0132	0.0418
	(0.68)	(1.36)	(0.86)	(1.16)	(0.59)	(1.02)	(0.46)	(0.99)	(0.30)	(0.91)
NEG_RES	0.1041**	0.1134**	0.1108**	0.1029**	0.0638	0.0729	0.1039**	0.1002**	0.1168***	0.1037**
	(2.05)	(2.11)	(2.44)	(2.25)	(1.49)	(1.64)	(2.14)	(2.03)	(2.69)	(2.37)
CONTENT_POS	0.0140	0.0317	-0.0304	0.0299	0.0713	0.1247*	0.1615	0.2063	0.1413	0.0987
	(0.24)	(0.57)	(-0.48)	(0.42)	(1.02)	(1.74)	(0.93)	(1.17)	(0.81)	(0.63)
CONTENT_NEG	0.1067*	0.0814	0.0346	0.0458	0.2012***	0.1823**	0.1118	0.0930	-0.1454	-0.0689
	(1.91)	(1.46)	(0.37)	(0.47)	(2.83)	(2.58)	(1.31)	(1.20)	(-1.42)	(-0.72)
INITIAL_STATUS		-0.0169		-0.0132		-0.0208*		-0.0143		-0.0088
		(-1.39)		(-1.21)		(-1.82)		(-1.28)		(-0.85)
RISING_STAR		-0.0375**		-0.0398**		-0.0373**		-0.0385**		-0.0413**
		(-2.25)		(-2.31)		(-2.24)		(-2.23)		(-2.42)
FALLEN_ANGEL		0.0852**		0.0841**		0.0737**		0.0863**		0.0787**
		(2.46)		(2.45)		(2.08)		(2.50)		(2.24)
LOCAL_MKT		-0.3724		-0.4111*		-0.3061		-0.4164*		-0.3952*
		(-1.59)		(-1.81)		(-1.41)		(-1.79)		(-1.81)
FX_RATE		-0.0794		-0.0227		-0.1624		-0.0178		-0.0700
		(-0.33)		(-0.10)		(-0.76)		(-0.07)		(-0.30)
US_MKT		-0.3180		-0.2788		-0.2863		-0.2864		-0.2621
		(-1.16)		(-1.02)		(-1.07)		(-1.14)		(-1.04)
TREASURY_MKT		-1.4634		-0.7329		-1.7181		-1.1664		-1.0144
		(-0.23)		(-0.12)		(-0.27)		(-0.18)		(-0.16)
VOLRISK_PREM		-0.2670**		-0.2710**		-0.2567*		-0.2669**		-0.2782**
		(-2.09)		(-2.15)		(-1.95)		(-2.09)		(-2.24)
ADS_INDEX		0.0351		0.0516		0.0565		0.0286		0.0373
		(0.24)		(0.35)		(0.39)		(0.20)		(0.27)
INTERCEPT	-0.0491*	-0.0508	-0.0496*	-0.0490	-0.0515*	-0.0494	-0.0498*	-0.0494	-0.0406	-0.0434
	(-1.66)	(-1.64)	(-1.66)	(-1.55)	(-1.79)	(-1.63)	(-1.68)	(-1.58)	(-1.43)	(-1.43)
N	166	166	166	166	166	166	166	166	166	166
Adj. R^2	0.13	0.31	0.14	0.31	0.16	0.33	0.14	0.31	0.17	0.33

Table 6. The Time-varying Information Value of Credit Rating Reports

This table presents the information value of tone conditional on different content categories in credit rating reports during credit rating changes before and after the 2009 Eurozone sovereign debt crisis. Subpanels (1) to (5) present the results for five content categories: Macroeconomic, Public & External Finance, Debt Dynamics, Financial Sector and Political & Institutional. The positive and negative tone related to each of these specific content categories are represented by CONTENT_POS and CONTENT_NEG in each subpanel. POS_RES and NEG_RES are the residual positive and negative tone related to other contents. 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 CDS(-1,1), which is the 3-day cumulative abnormal 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)									
	(1) Macroeconomic		(2) Public & Ext Finance		(3) Debt Dynamics		(4) Financial Sector		(5) Political & Institutional	
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
DOWN	0.0094	-0.0108	0.0119	-0.0078	0.0129	-0.0062	-0.0094	-0.0215	0.0063	-0.0054
	(0.48)	(-0.54)	(0.61)	(-0.39)	(0.68)	(-0.31)	(-0.45)	(-1.00)	(0.33)	(-0.29)
POS_RES	0.0667	0.0687	0.0599	0.0713	0.0366	0.0494	0.0509	0.0459	0.0419	0.0369
	(0.89)	(0.90)	(0.78)	(0.96)	(0.54)	(0.75)	(0.71)	(0.71)	(0.58)	(0.55)
NEG_RES	0.1009	0.1632**	0.1145*	0.1290*	0.0693	0.1016	0.0984*	0.1010	0.1504***	0.1460**
	(1.49)	(2.17)	(1.81)	(1.85)	(1.12)	(1.41)	(1.83)	(1.63)	(2.64)	(2.24)
CONTENT_POS	0.0262	0.0474	0.0271	-0.0232	0.0825	0.1138	0.0518	0.1084	0.3743	0.3547*
	(0.32)	(0.63)	(0.27)	(-0.24)	(0.87)	(1.22)	(0.18)	(0.37)	(1.62)	(1.68)
CONTENT_NEG	0.1278	0.0871	0.0851	0.1193	0.2023*	0.2122*	0.5607**	0.5933**	-0.1586	-0.0997
	(1.37)	(0.88)	(0.67)	(0.97)	(1.80)	(1.78)	(2.60)	(2.58)	(-0.91)	(-0.63)
POST2009	0.0624	0.1141	0.0650	0.1064	0.0428	0.0898	0.0574	0.0728	0.0826	0.0818
	(0.83)	(1.52)	(0.86)	(1.40)	(0.60)	(1.24)	(0.78)	(1.07)	(1.20)	(1.19)
POST2009xPOS_RES	-0.1017	-0.0582	-0.0616	-0.1393	-0.0542	-0.1002	-0.0811	-0.0636	-0.0895	-0.0523
	(-0.91)	(-0.51)	(-0.50)	(-1.17)	(-0.49)	(-0.91)	(-0.76)	(-0.64)	(-0.86)	(-0.52)
POST2009xNEG_RES	-0.0518	-0.1617	-0.0610	-0.1223	-0.0424	-0.1073	0.0076	-0.0311	-0.1014	-0.1220
	(-0.48)	(-1.53)	(-0.67)	(-1.32)	(-0.48)	(-1.14)	(0.08)	(-0.38)	(-1.21)	(-1.38)
POST2009xCONTENT_POS	-0.0567	-0.1866	-0.1419	0.0621	-0.0449	-0.0187	-0.0590	-0.2056	-0.7316**	-0.7911**
	(-0.41)	(-1.45)	(-1.09)	(0.45)	(-0.30)	(-0.14)	(-0.18)	(-0.58)	(-2.10)	(-2.55)
POST2009xCONTENT_NEG	-0.0777	-0.0943	-0.1550	-0.2505	-0.0450	-0.1305	-0.5788**	-0.6354**	-0.0235	0.0533
	(-0.68)	(-0.79)	(-0.85)	(-1.37)	(-0.30)	(-0.87)	(-2.52)	(-2.55)	(-0.11)	(0.27)
INITIAL_STATUS		-0.0220*		-0.0173		-0.0241**		-0.0156		-0.0137
		(-1.74)		(-1.53)		(-2.02)		(-1.39)		(-1.28)
RISING_STAR		-0.0415**		-0.0494***		-0.0398**		-0.0443**		-0.0420**
		(-2.47)		(-2.86)		(-2.33)		(-2.29)		(-2.56)
FALLEN_ANGEL		0.0877**		0.0854**		0.0759**		0.0893***		0.0808**
		(2.48)		(2.41)		(2.08)		(2.86)		(2.13)
LOCAL_MKT		-0.4068*		-0.4500**		-0.3357		-0.4145*		-0.4409**
		(-1.75)		(-2.00)		(-1.48)		(-1.84)		(-2.00)
FX_RATE		-0.0048		0.0430		-0.0844		-0.1783		-0.0014
		(-0.02)		(0.18)		(-0.36)		(-0.73)		(-0.01)
US_MKT		-0.3855		-0.3175		-0.3476		-0.0838		-0.2743
		(-1.36)		(-1.15)		(-1.27)		(-0.32)		(-1.10)
TREASURY_MKT		-1.8158		-1.1386		-1.6809		-3.4797		-1.8692
		(-0.27)		(-0.18)		(-0.26)		(-0.54)		(-0.29)
VOLRISK_PREM		-0.2882**		-0.2938**		-0.2606*		-0.2552**		-0.2953**
		(-2.14)		(-2.23)		(-1.87)		(-2.05)		(-2.30)
ADS_INDEX		0.0071		0.0324		0.0371		0.0361		0.0215
		(0.05)		(0.22)		(0.25)		(0.27)		(0.15)
INTERCEPT	-0.0644	-0.0619	-0.0666*	-0.0582	-0.0595	-0.0586	-0.0695*	-0.0585	-0.0654*	-0.0556
	(-1.65)	(-1.62)	(-1.69)	(-1.51)	(-1.61)	(-1.58)	(-1.71)	(-1.57)	(-1.69)	(-1.51)
N	166	166	166	166	166	166	166	166	166	166
Adj. R^2	0.14	0.33	0.15	0.33	0.16	0.34	0.18	0.37	0.19	0.36

Table 7. The Post-Announcement CDS Drifts

This table presents the information value of tone in Moody's credit rating reports in predicting future abnormal sovereign CDS spreads from 2003 to 2013. Panel A and Panel B show the results of similar portfolios formed 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, please 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 8. The Information Value of Tone during Other Credit Rating Actions

This table presents the information value of tone during credit rating changes, watchlist and outlook actions announced by Moody's from 2003 to 2013. 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 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
UP	-0.0348***	-0.0263**	-0.0149			-0.0116
	(-3.08)	(-2.31)	(-1.61)			(-0.98)
DOWN	-0.0025	-0.0002	-0.0088			-0.0068
	(-0.20)	(-0.02)	(-0.85)			(-0.53)
POS_WATCH	-0.0051	-0.0078		0.0088		-0.0009
	(-0.37)	(-0.56)		(0.71)		(-0.07)
NEG_WATCH	0.0110	0.0090		0.0077		0.0045
	(0.75)	(0.72)		(0.70)		(0.32)
POS_OUTLOOK	-0.0166	-0.0080			0.0144	0.0058
	(-1.54)	(-0.78)			(1.51)	(0.52)
NEG_OUTLOOK					0.0105	
					(0.81)	
POS			0.0036	0.0097	0.0016	0.0036
			(0.10)	(0.27)	(0.04)	(0.10)
NEG			0.0554*	0.0617**	0.0571*	0.0600**
			(1.91)	(2.43)	(1.89)	(2.05)
INITIAL_STATUS		-0.0026	-0.0032	-0.0035	-0.0025	-0.0032
		(-0.34)	(-0.42)	(-0.46)	(-0.33)	(-0.41)
RISING_STAR		-0.0003	-0.0006	-0.0078	-0.0039	-0.0009
		(-0.02)	(-0.04)	(-0.54)	(-0.27)	(-0.06)
FALLEN_ANGEL		0.0343	0.0281	0.0262	0.0256	0.0284
		(1.31)	(1.05)	(0.99)	(0.95)	(1.06)
LOCAL_MKT		-0.5240***	-0.5302***	-0.5208***	-0.5433***	-0.5370***
		(-2.90)	(-2.97)	(-2.91)	(-3.00)	(-2.97)
FX_RATE		-0.1991	-0.1598	-0.1740	-0.1629	-0.1468
		(-0.78)	(-0.62)	(-0.66)	(-0.63)	(-0.56)
US_MKT		-0.4461**	-0.4504**	-0.4784**	-0.4538**	-0.4539**
		(-2.10)	(-2.18)	(-2.31)	(-2.19)	(-2.20)
TREASURY_MKT		3.9089	4.1825	4.1298	3.9994	4.0436
		(0.93)	(1.01)	(0.97)	(0.93)	(0.96)
VOLRISK_PREM		-0.2218***	-0.2249***	-0.2218***	-0.2248***	-0.2243***
		(-3.53)	(-3.64)	(-3.53)	(-3.66)	(-3.53)
ADS_INDEX		-0.0002	0.0103	0.0003	0.0144	0.0090
		(-0.00)	(0.11)	(0.00)	(0.15)	(0.09)
INTERCEPT	0.0237**	0.0171*	-0.0071	-0.0193	-0.0222	-0.0126
	(2.17)	(1.70)	(-0.30)	(-0.84)	(-0.93)	(-0.50)
N	323	323	323	323	323	323
Adj. R^2	0.06	0.21	0.22	0.21	0.22	0.22

Table 9. The Information Value of Tone in Predicting Future Rating Actions

This table presents the information value of tone in Moody's credit rating reports and watchlist actions in predicting future rating changes from 2003 to 2013. Subpanel (1) presents the results for future rating downgrades within 1 year, while subpanel (2) presents the results for future rating downgrades within 2 years. The dependent variables are 1-YR FUTURE DOWNGRADE and 2-YR FUTURE DOWNGRADE. 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: Future Rating Downgrade					
	(1) Within 1 Year			(2) Within 2 Years		
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
UP	-0.1999***	-0.1991***	-0.0748*	-0.2357***	-0.2341***	-0.1018**
	(-4.48)	(-4.42)	(-1.81)	(-4.95)	(-4.90)	(-2.33)
DOWN	0.0868	0.0946	0.0365	0.1074	0.1095	0.0472
	(1.20)	(1.27)	(0.46)	(1.43)	(1.43)	(0.58)
POS_WATCH	-0.0543***	-0.0508***	-0.0012	-0.0640***	-0.0600***	-0.0090
	(-3.73)	(-3.33)	(-0.05)	(-3.99)	(-3.60)	(-0.36)
NEG_WATCH	0.5851***	0.5777***	0.5341***	0.5356***	0.5303***	0.4828***
	(7.52)	(7.38)	(6.46)	(6.71)	(6.63)	(5.74)
POS_OUTLOOK	-0.1910***	-0.1914***	-0.0733*	-0.2253***	-0.2249***	-0.0987**
	(-4.43)	(-4.41)	(-1.86)	(-4.88)	(-4.88)	(-2.36)
POS			-0.0380			-0.0540
			(-0.40)			(-0.54)
NEG			0.4649***			0.4862***
			(3.46)			(3.48)
INITIAL_STATUS		-0.0535	-0.0557		-0.0585	-0.0603
		(-1.46)	(-1.48)		(-1.55)	(-1.56)
RISING_STAR		0.0373	0.0356		0.0414	0.0403
		(1.09)	(1.50)		(1.07)	(1.55)
FALLEN_ANGEL		-0.1122	-0.1610		-0.0471	-0.0986
		(-0.67)	(-1.02)		(-0.26)	(-0.56)
INTERCEPT	0.2453***	0.2676***	0.0591	0.2892***	0.3125***	0.0990
	(4.63)	(4.69)	(0.70)	(5.16)	(5.17)	(1.12)
N	323	323	323	323	323	323
Adj. R^2	0.45	0.45	0.48	0.45	0.45	0.47

Table 10. The Information Value of Anticipated and Surprise Tone

This table presents the information value of anticipated and surprise tone. POS_P and NEG_P are the positive and negative anticipated tone, while POS_S and NEG_S are the positive and negative surprise tone. 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 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)				
	(1) Anticipated & Surprise Tone		(2) Tone Robustness to Lagged Sovereign Default Risk Variables		
Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
DOWN	0.0040	-0.0028	-0.0001	0.0133	0.0133
	(0.19)	(-0.14)	(-0.01)	(0.60)	(0.60)
POS			0.0520	0.0866	0.0864
			(1.12)	(1.65)	(1.64)
NEG			0.1005**	0.1077**	0.1075**
			(2.25)	(2.27)	(2.28)
POS_P	0.0146	0.0404			
	(0.31)	(0.80)			
NEG_P	0.1157**	0.1072**			
	(2.35)	(2.26)			
POS_S	0.0171	0.0610			
	(0.35)	(1.23)			
NEG_S	0.0913**	0.1041**			
	(2.00)	(2.10)			
CDS(-30,-2)					-0.0008
					(-0.06)
INITIAL_RATING				-0.0018	-0.0018
				(-0.57)	(-0.58)
RECENT_DEFAULT				0.0383**	0.0383**
				(2.33)	(2.32)
GDP_GROWTH				5.9555	5.9389
				(0.94)	(0.95)
DEBT_GDP				-0.0011	-0.0010
				(-0.07)	(-0.06)
FRES_GDP				0.0077	0.0076
				(0.17)	(0.17)
FRES_GROWTH				0.0308***	0.0308***
				(2.69)	(2.67)
FX_GROWTH				-0.0195	-0.0199
				(-0.38)	(-0.38)
TRADEBAL_GDP				-0.0577	-0.0574
				(-1.01)	(-1.01)
SP500				-0.2869**	-0.2872**
				(-2.16)	(-2.15)
FISCAL_FREEDOM				0.0000	0.0000
				(0.05)	(0.05)
MONETARY_FREEDOM				0.0009	0.0009
				(0.89)	(0.89)
FINANCIAL_FREEDOM				-0.0004	-0.0004
				(-0.83)	(-0.82)
HIGH_STRESS				-0.0076	-0.0075
				(-0.31)	(-0.31)
INITIAL_STATUS		-0.0131	-0.0138	-0.0353*	-0.0355*
		(-1.18)	(-1.29)	(-1.69)	(-1.68)
RISING_STAR		-0.0396**	-0.0396**	-0.0268	-0.0269
		(-2.30)	(-2.35)	(-1.34)	(-1.33)
FALLEN_ANGEL		0.0862**	0.0855**	0.0660*	0.0660*
		(2.43)	(2.49)	(1.87)	(1.87)
LOCAL_MKT		-0.4127*	-0.4097*	-0.4203**	-0.4208**
		(-1.82)	(-1.83)	(-2.17)	(-2.17)
FX_RATE		-0.0074	-0.0185	-0.0912	-0.0906
		(-0.03)	(-0.08)	(-0.38)	(-0.38)
US_MKT		-0.3192	-0.2994	-0.3057	-0.3081
		(-1.18)	(-1.13)	(-1.00)	(-0.95)
TREASURY_MKT		-1.0846	-0.8474	-5.4190	-5.3871
		(-0.17)	(-0.14)	(-0.73)	(-0.73)
VOLRISK_PREM		-0.2688**	-0.2692**	-0.2315*	-0.2313*
		(-2.07)	(-2.15)	(-1.78)	(-1.78)
ADS_INDEX		0.0411	0.0389	0.1706	0.1706
		(0.29)	(0.27)	(1.22)	(1.21)
INTERCEPT	-0.0451	-0.0492	-0.0495	-0.0913	-0.0908
	(-1.55)	(-1.60)	(-1.59)	(-1.10)	(-1.09)
N	166	166	166	166	166
Adj. R^2	0.14	0.31	0.31	0.40	0.40

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

This figure presents the mean net tone scores of Moody's credit rating reports sorted by report type: upgrades (UP), downgrades (DOWN), positive (POS WATCH) and negative watch (NEG WATCH), and positive (POS OUTLOOK) and negative outlook (NEG OUTLOOK).

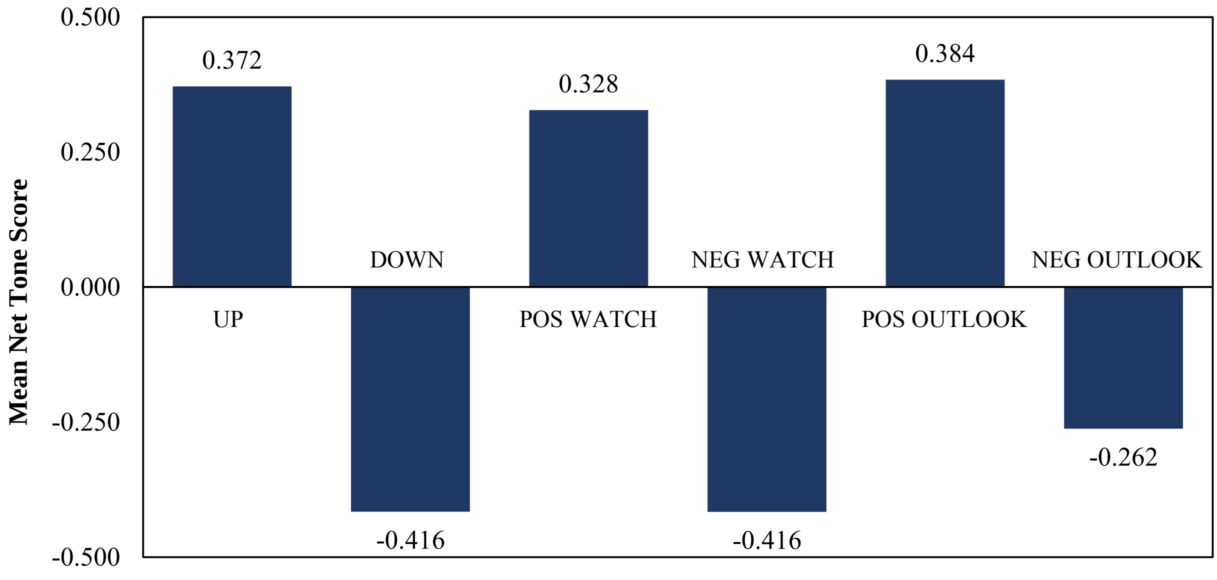


Figure 2: Variation in Mean Monthly Net Tone of Moody's Credit Rating Reports

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

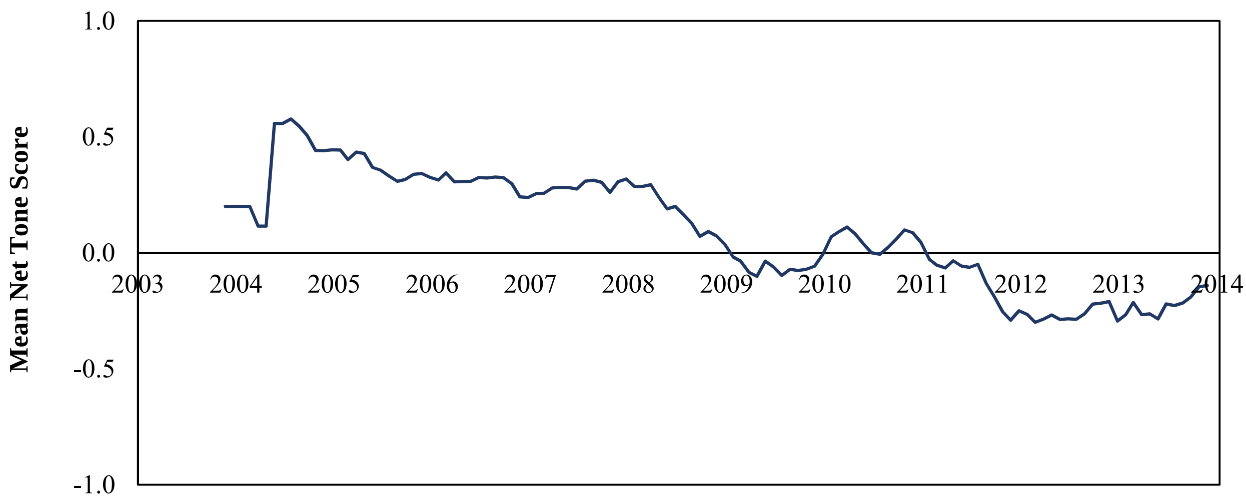
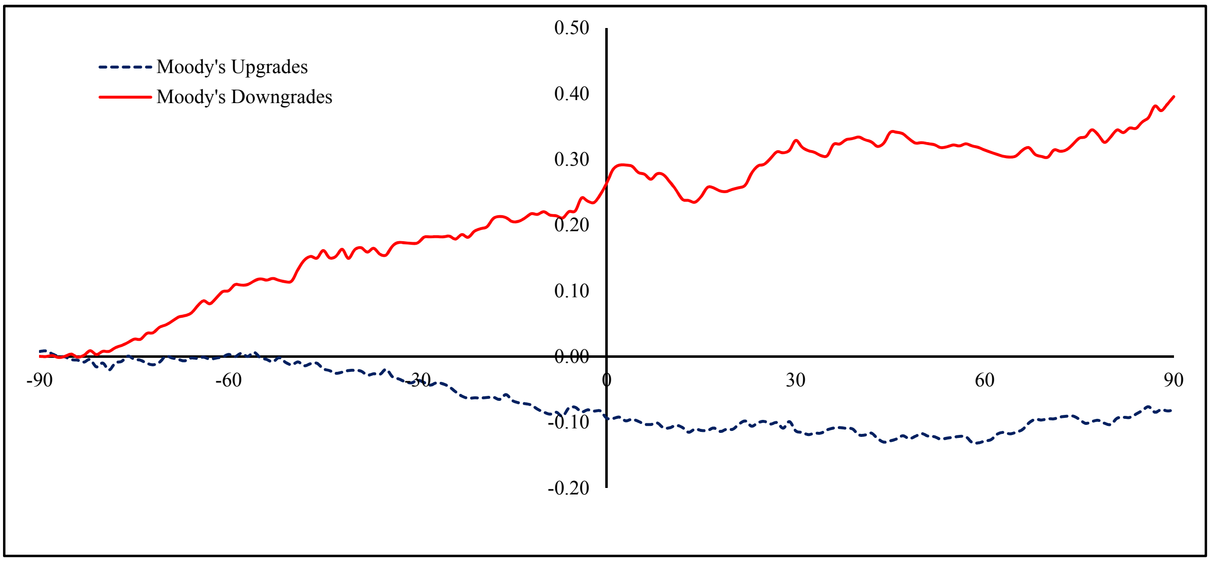


Figure 3: Cumulative Abnormal Sovereign CDS Spread Changes around Credit Rating Changes Announced by Moody's

This figure plots the mean daily cumulative abnormal sovereign CDS spread percentage changes of all event countries across the window [-90,90] for credit rating changes announced by Moody's from 2003 to 2013. The dotted blue and solid red lines correspond to Moody's upgrades and downgrades respectively.



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.
2-YR FUTURE DOWNGRADE	A dummy variable that equals 1 if there is a downgrade within two years 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	
DOWN	A dummy variable that equals 1 if there is a rating downgrade 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 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 and beyond) 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.
POS_P NEG_P	The anticipated components of positive and negative tone, estimated by the computation method described under Hypothesis 6 of our study.
Other Variables	
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.

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 a 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 this Appendix C, we provide a detailed description of our Naïve Bayesian machine learning algorithm, including the data preparation process, algorithm training, text classification process, and algorithm accuracy validation. We also describe the bootstrap technique that we apply in our testing of Hypothesis 2.

C.1. NAÏVE BAYESIAN MACHINE LEARNING ALGORITHM

This section describes our Naïve Bayesian machine learning algorithm.

Algorithm Basics

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

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

$$c^* = \operatorname*{argmax}_{c \in \{c_1, c_2, \dots, c_k\}} \frac{P(w \mid c)P(c)}{P(w)}$$

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

$$c^* = \operatorname*{argmax}_{c \in \{c_1, c_2, \dots, c_k\}} P(w \mid c)P(c)$$

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

$$c^* = \operatorname*{argmax}_{c \in \{c_1, c_2, \dots, c_k\}} P(c) \prod\nolimits_{j=1}^{n} P(w_j \mid c)$$

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

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

We use the Naïve Bayesian algorithm because of its advantages over the dictionary approach. First, the dictionary approach does not take into account the context of a sentence. For example, if the sentence is describing firm earnings, "increase" should be treated as a positive word. However, if the sentence is describing operational costs, then it should be considered as a negative word. Second, the Naïve Bayesian approach is domain-specific. It adapts to words that appear in texts and their probabilistic relation to a certain category. This results in increased classification accuracy for the specific context. Third, the dictionary approach assigns the same weight to all words in the dictionary, while the Naïve Bayesian approach utilizes the probabilistic relation between words and categories. The dictionary approach is therefore likely to underperform the Naïve Bayesian approach, a result which has been documented by Li (2010) and Huang, Zang and Zheng (2012). Finally, the dictionary approach relies on ready-built dictionaries, which are not always suitable for the type of text being analyzed. For example, the financial dictionaries developed by Loughran and McDonald (2011) are based on 10-K filings. While they may be well-suited to analyze corporate reports, they may not be entirely appropriate for sovereign credit rating reports. Furthermore, our study aims to conduct text classification along two dimensions involving tone and content categories, which cannot be readily implemented using a dictionary approach.

Tone and Content Categories

In our study, we perform text classification at the sentence level, since a sentence is a natural unit for expressing tone and opinion. As described earlier, each sentence in each report is classified along 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 the three major CRAs: 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]

Data Preparation

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 along the tone and content dimensions. Panel B 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. For 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]

Algorithm Training and Text Classification

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

Validation of Algorithm Accuracy

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 B2 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 have been discussed earlier in our main study.

C.2. BOOTSTRAP TECHNIQUE

This section explains the bootstrap technique described in Efron and Tibshirani (1993) and Hull, Predescu and White (2004), used in the testing of Hypothesis 2. Let the values sampled for the abnormal CDS spread change be $s_1, s_2, \dots, s_N$, the mean abnormal CDS spread change be $\bar{s}$, and the standard deviation be $\hat{\sigma}$. The bootstrap test of whether the mean abnormal CDS spread change is different from zero is based on the distribution of the t-statistic $t = \sqrt{n}(\bar{s}/\hat{\sigma})$. Let $\tilde{s}_i = s_i - \bar{s}$ for $i = 1, \dots, N$. Our null hypothesis is that the distribution of the abnormal CDS spread change corresponds to the distribution where $\tilde{s}_1, \tilde{s}_2, \dots, \tilde{s}_N$ are equally likely. We refer to this as the null distribution, which has a mean of zero. We then sample N times with replacement from the null distribution and calculate $t^B = \sqrt{n}(\bar{s}^B/\hat{\sigma}^B)$, where $\bar{s}^B$ and $\hat{\sigma}^B$ are the sample mean and standard deviation. We repeat this 1,000 times. This provides an empirical distribution for t under the null hypothesis. By comparing t with the appropriate percentile of this distribution, we can test whether the null hypothesis can be rejected at a particular significance level.

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 is then used to classify sentences in the credit rating reports into one of these 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 Impact of fiscal and monetary policies on external accounts 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 Debt 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 for 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 it 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