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Understanding sovereign credit ratings: Text-based evidence from the credit rating reports

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ABSTRACT

We apply a novel approach to identifying the qualitative judgment of the rating committee in sovereign credit ratings by extending the traditional regression with new measures – sentiment and subjectivity scores – obtained by textual sentiment analysis methods. Using an ordered logit with random effects for 98 countries from 1995 to 2018, we find evidence that the subjectivity score provides additional information not captured by previously identified determinants of sovereign credit ratings, even after controlling for political risk, institutional strength, and potential bias. The results from the bivariate and multivariate analysis confirm differences in textual sentiment and subjectivity between emerging markets and advanced economies, as well as before and after the 2008 global financial crisis.

1. Introduction

Sovereign credit ratings are important for a country since they imply its (credit) risk and thus impact the government's cost of financing when accessing international financial markets, as well as costs of financing for individuals residing in a particular country and firms exposed to a particular country's sovereign risk. Therefore, one would expect that a sovereign credit rating is assigned based on thoroughly developed criteria and supported by data. However, as many studies note, this represents only one part of the rating, the so-called hard information (Cantor and Packer, 1996; Afonso, 2003; Butler and Fauver, 2006; Afonso et al., 2009; Özturk, 2014). The other (soft) part of the rating reflects the qualitative judgment or interpretation of the rating committee. The leading credit rating agencies themselves (Standard & Poor's, 2017; Moody's, 2016; Fitch, 2017) note that their sovereign ratings are merely an opinion and are assigned based on various quantitative factors and some qualitative reasoning.

Whereas the majority of studies tried to identify the determinants of sovereign credit ratings using macroeconomic explanatory variables (e.g. Cantor and Packer, 1996; Afonso, 2003), some prior studies also focused on the soft part of the rating by including explanatory variables that gauge political risk (e.g. Özturk, 2014). Some note that sovereign credit ratings are biased, as rating agencies favor their home countries or those close to them and disfavor emerging markets (Fuchs and Gehring, 2017; Zheng, 2012; De Moor et al., 2018). This bias seems substantial and mostly downward for emerging markets and upward for advanced countries.

A question arises, whether it is possible to disentangle bias and soft information? While some studies do not distinguish between those terms (e.g. Özturk, 2014), others make a clear distinction (e.g. De Moor et al., 2018). We believe the latter approach is more appropriate. Thus, we hypothesize that the soft information represents factors that are objectively unobservable but can affect the country's ability to repay its debt, e.g., governance and institutional quality. Several proxies for these factors are available

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(e.g., ICRG,[2] WGI[3]), but are usually based on expert or public opinion and thus subjective. We also identify factors that may affect the rating committee's decision but by definition, do not affect the country's creditworthiness and are thus potential sources of bias, e.g. economic and cultural proximity. A qualitative judgment of the rating committee is thus defined as a subjective interpretation of soft information and may contain potential bias. For example, if the rating committee considers the level of corruption in a particular country when assigning credit ratings, that falls into the soft information category and does not necessarily lead to biased sovereign credit ratings. On the other hand, if the rating committee (albeit unintentionally) weighs in cultural similarities or differences, that is considered a bias.

All prior findings are based on examining the sovereign credit ratings themselves. However, credit ratings are accompanied by a rating report or an elaborate explanation motivating the rating or the rating change. This raises the question of whether it is possible to extract sentiment or tone reflecting the above-mentioned qualitative judgment from those reports. To answer this question, we propose a different approach, namely textual analysis, which is becoming more extensively used in corporate finance when it comes to analyzing public corporate disclosures/filings, media articles, and internet messages (Loughran and McDonald, 2016; Kearney and Liu, 2014).

The main contributions of this paper are twofold: methodological and practical. First, we build on the existing literature on identifying the determinants of sovereign credit ratings but extend the traditional approach further by exploiting the textual analysis angle. To our knowledge, only one study (Agarwal et al., 2019) applies a similar approach. We thus include two key groups of variables in our analysis, namely textual sentiment scores and subjectivity scores, which we acquire by applying textual analysis methods to S&P Rating Action and Full Reports, Fitch Rating Action and Full Reports, and Moody's Rating Action reports. The former is a group of indicators that measure negativity or positivity in texts, while the latter measures the degree of subjectivity in texts. We speculate that the sentiment score captures the general current perception of a country, while the qualitative judgment of the rating committee manifests itself in the subjectivity indicator. The aim is to answer to what extent sentiment/subjectivity affect sovereign credit ratings across countries and over time. We examine two main groups of countries, namely emerging markets and advanced economies, due to previously identified biases in the literature. We also explore the behavior of our key variables before and after the 2008 global financial crisis.

Second, having identified the relative importance of sovereign credit ratings and their effect on countries' cost of financing, we believe this research is important, as it significantly contributes to understanding sovereign credit ratings and their formation. It sheds new light on the characteristics of bond markets, especially for emerging markets, a field that has not been studied thoroughly before. It offers important insights for policymakers, regulators, private and professional investors, and financial institutions. A thorough understanding of sovereign credit ratings is crucial for (i) investors to be able to make fully informed investment decisions, (ii) policymakers to be able to adjust policy measures to obtain a more favorable rating for the country's debt issues, and (iii) to financial institutions who hold a substantial part of government bonds on their balance sheets.

The first objective of this paper is thus to determine whether sentiment or subjectivity scores offer any additional information not captured by the previously identified determinants of sovereign credit ratings, using a sample of 97 countries for the period of 2002–2018 by S&P, 98 countries for the period of 1999–2018 by Fitch, and 100 countries for the period of 1995–2018 by Moody's. We find that soft information proxies greatly enhance the predictability of sovereign credit ratings, which supports the existing findings of Özturk (2014), Mellios and Paget-Blanc (2006) and Haque et al. (1998), who argue that including political variables has a strong impact on modeled ratings. We find evidence of economic proximity bias but no indication of cultural proximity bias. This is partly consistent with previous studies, including De Moor et al. (2018), Luitel et al. (2016), and Fuchs and Gehring (2017), who detect both proximity and cultural bias.

After adding the indicators for textual sentiment and subjectivity, the results support our initial hypothesis that textual sentiment mirrors the general opinion of a country and retains explanatory power after including relevant determinants for institutional and political risk, as well as a potential bias. Furthermore, we find evidence that the qualitative judgment of the rating committee is expressed in the credit rating reports and reflected in the subjectivity score, especially when political risk variables are not included in the models.

The second objective of this paper is to investigate the existence of differences in sentiment or subjectivity measures between emerging and advanced markets. We find significant differences in sentiment for one of the agencies, which implies differences in the general opinion of groups of countries, but not the remaining two agencies. We also find evidence of differences in the subjectivity scores between groups of countries, implying that the rating committee employs qualitative judgment of different magnitudes. We also run separate regressions for advanced and emerging markets. Even though the results are not statistically significant, there are substantial differences in coefficients for sentiment and subjectivity between advanced and emerging countries, supporting our previous finding. Additionally, we observe different determinants of sovereign credit ratings for both groups of countries, indicating the application of different weights to the qualitative judgment (Fuchs and Gehring, 2017; Zheng, 2012). The differences are in line with Yalta and Yalta (2018), Bissoondoyal-Bheenick (2005), and Afonso (2003). The latter identifies GDP per capita as the most important explanatory variable for advanced countries and external debt for emerging markets. We also find evidence of an bias for advanced countries, similar to Yalta and Yalta (2018) and Gültekin-Karakaş et al. (2011), who argue that high-income (advanced) countries receive more favorable ratings compared to low-income (emerging) countries, holding all else constant.

The final objective is to explore the drivers behind the sentiment and subjectivity scores. We find evidence supporting our previous findings since sentiment can be described by soft information, which reflect the general opinion of the country, and potential

[2] International Country Risk Guide by PRS Group.

[3] World Governance Indicators by World Bank.

bias proxies, while subjectivity remains almost unexplained. This is in line with Vernazza and Nielsen (2015), who conclude that the subjective component in credit ratings is detrimental because it seems unrelated to the country's true credit risk.

The remainder of the paper is structured as follows. In section two, we provide a relatively extensive overview of relevant prior literature on determinants of sovereign credit ratings and textual sentiment analysis. We describe the data and methodological framework in sections three and four, respectively. Next, in section five, we discuss the overall results. More specifically, we examine the differences in sentiment and subjectivity measures between emerging and advanced economies, as well as before and after the onset of the global financial crisis. Furthermore, we investigate the potential determinants of sentiment and subjectivity indicators. Section six concludes.

2. Literature review

Governments generally seek credit ratings to gain access to international capital markets, where institutional investors are limited to investing in rated (most often even investment grade rated) securities (Cantor and Packer, 1996). Credit rating agencies (CRAs) estimate countries' creditworthiness (the relative likelihood that a borrower will default on its obligations) by assigning sovereign credit ratings. The rating committee takes into account key economic factors that, together with some qualitative judgment, determine the creditworthiness in order to assign sovereign credit rating (Reusens and Croux, 2017). According to Kiff et al. (2010) the relative importance of these factors is not fixed but can vary over time, depending on new information and economic environment. Reusens and Croux (2017) point out that even though the CRAs publicly disclose the components of sovereign credit ratings, the rating committee typically makes additional arbitrary modifications to it.

While the official rating methodologies of CRAs are generally similar, some subtle differences demonstrate the role of qualitative assessment and subjectivity in sovereign credit ratings. According to Standard & Poor's (2017), they assess five main factors that form the foundation of their sovereign credit analysis.[4] Each assessment is based on an array of quantitative factors and qualitative considerations. Despite increased transparency of the (objective) credit rating procedure, they state that qualitative assessment still plays a significant part in the process, as they consider various adjustments, trends and other factors that can cause a deviation from the indicative rating. Similarly, Moody's (2016) claim that the initial sovereign credit rating is based on four key factors.[5] Despite revealing the importance of these factors, they stress that the actual weights may differ due to qualitative reasoning. Fitch's (2017) approach to sovereign credit ratings is also a combination of quantitative and qualitative judgments. They rely on four analytical pillars.[6] They employ its 'Sovereign Rating Model' as the starting point for assigning sovereign ratings.[7] However, since no model perfectly captures all the relevant information, the rating committee also adjusts for factors not reflected by the model.

This suggests that sovereign credit ratings are driven by a combination of hard and soft information, as has been argued in a number of studies on the determinants of sovereign credit ratings (e.g. Cantor and Packer, 1996; Afonso, 2003; Butler and Fauver, 2006; Afonso et al., 2009; Özturk, 2014). Cantor and Packer (1996) were the first to investigate the determinants and impact of sovereign credit ratings. They state that identifying the relationship between CRA's criteria and actual ratings is difficult, in part because some of the criteria are not quantifiable. A total of eight factors are identified as possible determinants in assigning a country's credit rating.[8] They find that all, but fiscal and external balance, appear to play an important role in determining a country's credit rating.[9] Even though fiscal and external balances are not statistically significant in their results, they may still influence the rating, where both, a larger fiscal and external balance, lead to a higher risk of default. Butler and Fauver (2006) examine the cross-sectional determinants of sovereign credit ratings and how the efficiency of a country's legal and political institutions affects its sovereign credit rating. Their findings suggest that the quality of a country's legal and political institutions has a strong positive effect on sovereign credit ratings, whereby controlling for macroeconomic factors.[10] Vernazza and Nielsen (2015) state that credit ratings comprise of objective and subjective components. They break down the credit ratings into objective and subjective part. They try to predict short- and long-term defaults and conclude that while the objective part is able to predict sovereign defaults, the subjective part is not.

The general finding of prior research shows that identification of the hard information part of a credit rating is relatively straightforward and based on relevant macroeconomic and fiscal variables. Additionally, to a limited extent, soft information can be proxied by political risk variables. But in order to identify the remaining soft information content and its effect, a more complex research approach is needed. This part of the ratings to a large extent reflects the sentiment or perception (interpretation) of the rating committee. Thus, two countries with similar exposure to macroeconomic shocks and comparable political risk may have substantially different credit ratings. However, the relative importance of the soft part is ambiguous (Amstad and Packer, 2015;

[4] Institutional and governance effectiveness and security risks (reflected in the institutional assessment), economic structure and growth prospects (economic assessment), external liquidity and international investment position (external assessment), fiscal performance and flexibility as well as debt burden (fiscal assessment), and monetary flexibility (monetary assessment). They assign an assessment to each of the five factors on a six-point numerical scale, where 1 is the strongest, and 6 is the weakest.

[5] Economic strength, institutional strength, fiscal strength, and susceptibility to event risk. The total number of sub-factor indicators is 14. These indicators are mapped to one of 15 ranking categories, ranging from Very High Plus (VH+) to Very Low Minus (VL-).

[6] Structural features, macroeconomic performance, policies and prospects, public finances, and external finances, where structural features usually have the highest weights.

[7] It is a multiple regression-based rating model that makes use of historical, current, and forward-looking data for 18 key variables.

[8] Per capita income, GDP growth, inflation, fiscal balance, external balance, external debt, level of economic development, and default history.

[9] Afonso (2003) extends their analysis and confirms these results.

[10] Such as GDP per capita, inflation, foreign debt per GDP, previous defaults, and general development.

Bruner and Abdelal, 2005; Luitel et al., 2016). There already exists a fair body of literature examining the qualitative judgment or soft information in sovereign credit ratings. A large part of that literature discusses the impact of qualitative judgment from the perspective of subjectivity that leads to biased sovereign credit ratings. Prior literature either finds that rating agencies assign a higher rating to their home country relative to foreign countries, or that rating agencies favor countries that are close to them or that rating agencies under-rate emerging markets (for an extended overview see e.g. Luitel et al., 2016).

Luitel et al. (2016) note that the sovereign ratings differ depending on the rating agency's home country. They find evidence that US rating agencies favor countries that have stronger geopolitical and trade ties with the US. This is supported by Fuchs and Gehring (2017) who find that agencies assign higher ratings to their home countries, those with similar cultural interests, and those to which home countries have the highest risk exposure. Similarly, Zheng (2012) argues that Dagong[11] tends to rate non-Western countries higher than S&P. This discrepancy can be explained by different perceptions. Additionally, Luitel et al. (2016) notice that emerging markets receive relatively low ratings and very frequent rating downgrades. Gültekin-Karakaş et al. (2011) show the discrepancies between advanced and emerging countries, indicating that rating agencies disfavor emerging markets relative to advanced markets. De Moor et al. (2018) find that the subjective component of a credit rating is substantial, especially for the lower rating classes (thus mainly emerging markets). Özturk (2014) finds that common language influences sovereign credit ratings upwards. Proença et al. (2021) find that all main rating agencies exhibit regional bias, that is clustering of countries when it comes to sovereign credit ratings. Overes and van der Wel (2023) also find higher regulatory quality and higher GDP per capita to be associated with higher credit rating. It also seems that the behavior of credit rating agencies is driven by reputational concerns and has changed after the global financial crisis. Huang and Shen (2021), for example, argue that agencies are driven by safety concerns in a therefore exhibit hearding behavior when assigning ratings — it they make an error in judgment, this assures that all the agencies are at least making a similar error. Huang and Shen (2021) also show that in the post global financial crisis period, safety concern is driving the behavior of agencies, such that they have become more conservative. Finally, Cuadros-Solas and Salvador Muñoz (2022) argue that a significant part of the rating adjustments is due to changes in rating policies. Hence, ample amount of existing literature provide solid evidence that credit rating agencies are not objectively assigning credit ratings due to various reasons, ranging from a embedded biases to reputational concerns.

Studies predominantly use macroeconomic explanatory variables, whereas some argue that political risk variables should be taken into account as well. Mellios and Paget-Blanc (2006) start by including a corruption perception index as a proxy for political risk, which has a strong influence on ratings. Özturk (2014) builds on this finding by using governance indicators as proxies for political risk and finds a positive relationship between institutional quality and sovereign credit ratings. While sovereign credit ratings have been analyzed in order to identify the subjective component using various proxies for either soft information or bias, almost no studies have examined the reports which offer the explanation behind the assigned ratings. Textual methods can be applied to these reports in order to extract sentiment or tone, which in turn may help in examining the nature of the subjective (qualitative) component.

A body of literature already exists on the impact of sentiment or tone (qualitative information) in corporate annual and credit rating reports on corporate equity valuation (Loughran and McDonald, 2016; Kearney and Liu, 2014; Agarwal et al., 2016), but the evidence on the impact of sovereign credit rating reports on e.g., sovereign debt market is practically non-existent. Sovereign credit ratings can have economically more important consequences than firm-level credit ratings since they typically affect the efficiency and stability of capital markets within and across countries. To our knowledge, only one study applies textual analysis methods to these reports. Agarwal et al. (2019) find that a negative tone in the reports gives additional information not detected in credit ratings alone. Their finding is substantial, as it shows a new determinant of sovereign credit risk that is not captured by the usual quantitative credit rating analysis. Additionally, they show that content on negative debt dynamics is the most informative. There is somewhat more existing research if we extend the scope of analysis to credit rating reports in general. Agarwal et al. (2016) find that net sentiment or linguistic tone is negatively related to abnormal returns and can predict rating changes. Kiesel (2021) finds a relation between the tone of credit rating reports and equity or CDS markets, where a negative sentiment in the text results in a negative market reaction. Löffler et al. (2021) investigate whether and how the linguistic tone of Moody's rating reports affects the stock market in the United States and find a significant short-term market impact of net tone. They conclude that investors overreact to the net tone of rating reports.

While prior literature tried to identify the determinants of sovereign credit ratings using various classical estimation techniques, a large part of the ratings was still left unexplained, and the percentages of correctly predicted sovereign credit ratings were relatively low. We propose an alternative approach. Due to the lack of prior evidence of the information value of sovereign credit rating reports, the objective is to exploit this under-utilized source of qualitative data to gain new insights into the formation of credit ratings. We thus aim to address the following research problem: To what extent does sentiment or subjectivity affect sovereign credit ratings across countries and over time? In order to estimate the extent of this effect, we will analyze reports issued by S&P, Fitch, and Moody's credit rating agency by applying textual analysis methods and explore to what extent different sentiment and subjectivity measures relate to the ratings. Taking into account the before-mentioned studies on bias in sovereign credit ratings, we focus our analysis on the comparison of two groups of countries: emerging markets and advanced economies. We hypothesize that emerging markets will have higher sentiment and subjectivity scores than advanced economies because data is limited and/or potentially unreliable, which leads to the qualitative judgment of the credit rating committee having a greater role in the rating process. Furthermore, we hypothesize the sentiment and subjectivity scores will likely change after the global financial crisis of

[11] Chinese credit rating agency.

2008 because of increased demand for transparency of the rating process and recent criticism of the credit rating agencies that they inflated particular sovereign credit ratings (Agarwal et al., 2019; Gaillard, 2012), leading to more realistic perceptions of country risk.

3. Data

The major providers of sovereign credit ratings are the three biggest credit rating agencies, Standard and Poor's (S&P), Moody's, and Fitch. Historical credit ratings are available at Thomson Reuters Eikon, with the earliest rating being assigned in 1941 to the United States. However, most countries got their first-time rating in the 1990s or 2000s. We focus on long-term foreign currency sovereign ratings assigned by the three credit rating agencies, namely to 97 countries from 2002 to 2018 by S&P, to 98 countries from 1999 to 2018 by Fitch, and to 100 countries from 1995 to 2018 by Moody's, due to the availability of sovereign credit rating reports for these periods. CRAs generally review the assigned ratings once a year, except under extreme circumstances (e.g. a country is in selective default), and either affirm or change the rating. For this reason, we are working with yearly data. For the few occurrences when the ratings are changed more than once in a calendar year, we take the last assigned rating in that year. There are 35 advanced countries in all three samples, 62 emerging countries in the S&P sample, 63 emerging countries in the Fitch sample, and 65 emerging countries in Moody's sample.[12] The list of countries included in the analysis is provided in Appendix (Table A.11).

The countries are rated both as investment grade (ratings AAA[13]/Aaa[14] through BBB-/Baa3) and speculative grade (ratings BB+/Ba1 through D/C), with AAA/Aaa being the highest possible rating and D/C the lowest. For the purposes of quantitative analysis, as is accustomed in previous work on credit ratings, the ratings are transformed to an ordinal numerical scale ranging from 1 to 21, with 21 corresponding to AAA/Aaa rating and 1 corresponding to a D/C rating.

The dataset consists of twenty-six variables, as described in Table 1. Apart from the textual sentiment analysis in order to obtain proxies for the qualitative judgment of the rating committee, we control for traditionally considered macroeconomic explanatory variables, as well as country risk indicators. More specifically, to control for potential bias identified in the prior literature (Luitel et al., 2016; Fuchs and Gehring, 2017; Gültekin-Karakaş et al., 2011; Özturk, 2014), we consider additional controls, namely (economic and cultural) proximity variables in line with De Moor et al. (2018). There are discussed in more detail in the following subsections. We present the summary statistics in Table 2.

3.1. Textual sentiment analysis

Kearney and Liu (2014) define sentiment or tone as the degree of positivity or negativity in texts. They argue that sentiment can include both subjective judgment and objective reflection of economic conditions. The change in a credit rating is typically explained in an elaborate (text) report. Using textual analysis methods, one can analyze the reports and explore to what extent different sentiment measures relate to the ratings.

Textual analysis also referred to as content analysis, computational linguistics, and natural language processing, is defined by Stone et al. (1966) as any technique that objectively and systematically identifies specified text properties, which can then be used for inference. There are various textual analysis approaches, ranging from very basic dictionary-based approaches to more advanced machine-learning techniques. With dictionary-based methods, a computer processes the text and classifies words, phrases, or sentences into groups based on the user-defined dictionary or list (Li, 2010). It is also known as the 'bag-of-words' approach because texts can be viewed as the bag of words, and the structure, along with any linear ordering of words within the context, is ignored (Manning et al., 1999). On the other hand, machine learning, pioneered by computer scientists and mathematicians, relies on statistical techniques to infer the content of texts and to classify them based on statistical inference (Li, 2010). A detailed comparison of different approaches is beyond the scope of this paper.

We use the dictionary-based approach using the LM financial dictionary by Loughran and McDonald (2011). Initially, most researchers used well-established dictionaries such as General Inquirer (GI) or DICTION. Kearney and Liu (2014) stress that these are general English language linguistic dictionaries rather than dictionaries that are specific to the finance domain. Loughran and McDonald (2011) find that almost three-quarters of negative words in GI/DICTION are typically not negative in the financial context. They conclude that the use of dictionaries derived outside the finance domain has the potential for errors that are not simply white noise. Consequently, researchers constructed finance-specific dictionaries, such as LM, which led to more accurate and efficient sentiment scores. Additionally, as in most studies, we apply proportional weighting of words, where every word is assumed to be equally important.

We collected Rating Action reports and Full Rating reports by S&P, available between 2002 and 2018, Rating Action reports and Full Rating reports by Fitch, available between 1999 and 2018; and Rating Action reports by Moody's, available between 1995 and 2018. These form the corpus for various textual analysis techniques.

The process of using the dictionary-based approach to extract sentiment from reports is the following: The first step is to obtain the appropriate texts which form the corpus. Next, the dictionary (and sentiment categories) and the textual analysis program are selected. As already mentioned, we first exploit the LM financial dictionary, where we base our text features on the positive and

[12] Based on the IMF classification.

[13] S&P/Fitch credit rating scale.

[14] Moody's credit rating scale.

Table 1
Definitions and sources of variables.

Variable	Description	Source
Macroeconomic and fiscal strength		
Credit rating	Long-term issuer default rating (foreign)	Thomson Reuters Eikon
GDP per capita	Nominal GDP in 000 USD divided by midyear population	IMF World Economic Outlook Database
Real GDP growth	Yearly real GDP growth rate	IMF World Economic Outlook Database
Inflation	Inflation, average consumer prices (year-on-year changes in %)	IMF World Economic Outlook Database
Current account/GDP	Current account balance in USD (% of nominal GDP)	IMF World Economic Outlook Database
Trade/GDP	External trade of the country in USD (% of nominal GDP)	World Bank
External debt	Gross external debt position in USD (% of nominal GDP)	World Bank/World Bank QEDS
Economic development	Dummy variable: 1 if a country is classified as advanced by IMF, zero otherwise	IMF
Default history	Dummy variable: 1 in the year of default and thereafter, zero otherwise	Moody's and Fitch Sovereign default and recovery rates
Log of int. reserves	Natural logarithm of foreign currency reserves in million USD	IMF International Financial Statistics
Government debt/GDP	General government gross debt (% of nominal GDP)	IMF World Economic Outlook Database
Budget balance/GDP	General government net lending(+)/borrowing(–) - budget surplus or deficit balance in USD (% of nominal GDP)	IMF World Economic Outlook Database
Institutional strength and political risk - Soft information		
Institutional quality	Composite indicator that includes indicators for law and order, bureaucracy quality, democratic accountability and corruption	International country risk guide Table 3B
Governance	Composite indicator that includes indicators for government stability, socio-economic conditions, and investment profile	International country risk guide Table 3B
Economic and cultural proximity - Proxies for bias		
Trade proximity	Trade intensity of a country with the USA	OECD/WITS
Common language	Dummy variable: 1 if English is the common official language, zero otherwise	CEPII
Religious proximity	The probability that two randomly chosen individuals in the USA and a particular country share the same religion	World Religion Data (Correlates of War)
Geographical distance	Physical distance (in km) based on latitude and longitude from Washington DC (U.S.) to the capital city of a country divided by 100	CEPII
Textual sentiment analysis		
Net sentiment (W, dict)	Net textual sentiment/tone, measured as the difference between positive and negative sentiment, in %	S&P, Fitch & Moody's[a]
Negative sentiment	Negative textual sentiment/tone, measured as % of negative words in the credit rating report, in %	S&P, Fitch & Moody's[a]
Positive sentiment	Positive textual sentiment/tone, measured as % of positive words in the credit rating report, in %	S&P, Fitch & Moody's[a]
Polarity (W, dict)	Count of positive words minus the count of negative words, divided by the sum of positive and negative word counts, dictionary approach	S&P, Fitch & Moody's[a]
Polarity (S, ML)	Count of positive sentences minus the count of negative sentences, divided by the sum of positive and negative sentences counts, machine learning approach	S&P, Fitch & Moody's[a]
Subjectivity (W, dict)	Degree of subjectivity, measured as % of subjective words in the credit rating report, dictionary approach, in %	S&P, Fitch & Moody's[a]
Subjectivity (S, dict)	Degree of subjectivity, measured as % of subjective sentences in the credit rating report, dictionary approach	S&P, Fitch & Moody's[a]
Subjectivity (S, ML)	Degree of subjectivity, measured as % of subjective sentences in the credit rating report, machine learning approach	S&P, Fitch & Moody's[a]

[a] S&P Full Rating Reports and Rating Action reports, Fitch Full Rating Reports and Rating Action reports, Moody's Rating Action reports.

negative sentiment categories. Subsequently, sentiment scores are retrieved by running the program (we use Python). Our measure is the ratio (percentage) of the words in a given sentiment category to the total number of words in the text. We make two assumptions: (i) if more than one report is published in a calendar year, we take the sentiment from the last report in that year (similarly as with more than one sovereign credit rating per year); and (ii) if no reports are published in a calendar year, we assume there was no change in the prevailing sentiment/perception and take the value from the previous year. Finally, together with other variables, we use these measures in further analysis.

Based on the dictionary approach, we construct two different sentiment measures. First, we use (net) sentiment, which is defined as the difference between positive and negative sentiment, where negative (positive) sentiment is calculated as the ratio between the number of negative (positive) words and the total number of words in the text. As our second measure, we use polarity, defined as:

$$Polarity_{i,t} = \frac{pos_{i,t} - neg_{i,t}}{pos_{i,t} + neg_{i,t}} \tag{1}$$

where $pos_{i,t}$ is the count of positive words and $neg_{i,t}$ is the count of negative words in the text.

The LM dictionary also includes categories for 'uncertainty' (terms expressing imprecision rather than exclusively focusing on risk), 'strong modal', and 'weak modal' words (terms expressing levels of confidence). Therefore, as an alternative to polarity

Table 2
Summary statistics.

	Obs	Mean	St. Dev.	Median	Min	Max
S&P						
Credit rating	1382	13.241	5.143	13.000	1.000	21.000
GDP per capita	1382	19.225	21.609	9.202	0.330	120.449
Real GDP growth	1382	0.035	0.035	0.034	−0.151	0.251
Inflation	1382	0.048	0.056	0.032	−0.037	0.592
Current account/GDP	1382	−0.011	0.076	−0.012	−0.635	0.336
Trade/GDP	1382	0.923	0.658	0.748	0.207	4.426
External debt/GDP	1382	1.688	5.335	0.624	0.036	67.677
Economic development	1382	0.399	0.490	0.000	0.000	1.000
Default history	1382	0.158	0.365	0.000	0.000	1.000
Log of int. reserves	1382	9.856	1.766	9.900	5.326	15.169
Government debt/GDP	1382	0.537	0.361	0.447	0.001	2.371
Budget balance/GDP	1382	−0.023	0.042	−0.024	−0.320	0.305
Institutional quality	1382	14.153	4.191	13.500	6.000	22.000
Governance	1382	23.348	4.236	23.083	13.375	34.000
Trade proximity	1382	0.011	0.026	0.002	0.000	0.190
Common language	1382	0.242	0.428	0.000	0.000	1.000
Religious proximity	1382	0.526	0.222	0.625	0.012	0.780
Geographical distance	1382	80.895	35.097	74.148	0.000	163.711
Net sentiment	1382	−1.330	2.029	−0.985	−8.730	4.260
Negative sentiment	1382	4.221	1.472	3.920	1.360	10.110
Positive sentiment	1382	2.891	1.133	2.810	0.000	6.910
Polarity (dict)	1382	−0.181	0.266	−0.152	−1.000	0.611
Polarity (ML)	1382	0.419	0.288	0.460	−1.000	1.000
Subjectivity	1382	2.703	0.929	2.640	0.250	6.530
Subjectivity (LM)	1382	0.342	0.100	0.333	0.042	0.712
Subjectivity (ML)	1382	0.345	0.094	0.333	0.094	0.679
Fitch						
Credit rating	1433	13.373	5.169	13.000	1.000	21.000
GDP per capita	1433	19.053	21.456	9.261	0.245	120.449
Real GDP growth	1433	0.035	0.037	0.034	−0.151	0.345
Inflation	1433	0.049	0.062	0.032	−0.037	0.857
Current account/GDP	1433	−0.011	0.076	−0.013	−0.635	0.336
Trade/GDP	1433	0.911	0.656	0.725	0.207	4.426
External debt/GDP	1433	1.694	5.292	0.649	0.039	67.677
Economic development	1433	0.412	0.492	0.000	0.000	1.000
Default history	1433	0.152	0.359	0.000	0.000	1.000
Log of int. reserves	1433	9.817	1.836	9.952	4.083	15.169
Government debt/GDP	1433	0.537	0.358	0.447	0.001	2.371
Budget balance/GDP	1433	−0.022	0.043	−0.024	−0.320	0.305
Institutional quality	1433	14.324	4.176	13.833	6.000	22.000
Governance	1433	23.487	4.263	23.125	12.375	34.000
Trade proximity	1433	0.011	0.028	0.002	0.000	0.201
Common language	1433	0.229	0.420	0.000	0.000	1.000
Religious proximity	1433	0.531	0.223	0.633	0.012	0.805
Geographical distance	1433	81.015	34.393	73.478	0.000	163.711
Net sentiment (W, dict)	1433	−1.783	2.372	−1.700	−13.540	5.590
Negative sentiment	1433	4.922	1.784	4.740	0.330	14.950
Positive sentiment	1433	3.139	1.161	3.040	0.000	7.110
Polarity (W, dict)	1433	−0.206	0.275	−0.214	−1.000	0.778
Polarity (S, ML)	1433	0.390	0.290	0.405	−1.000	1.000
Subjectivity (W, dict)	1433	3.135	1.188	3.120	0.000	7.790
Subjectivity (S, dict)	1433	0.369	0.121	0.375	0.000	0.889
Subjectivity (S, ML)	1433	0.363	0.127	0.355	0.000	0.789

(*continued on next page*)

(positive/negative sentiment), we also introduce the subjectivity indicator. First, we define a new, wider category for 'subjectivity' that consists of the three before-mentioned categories. We then repeat the process described above using the newly constructed word list and apply the same assumptions. We obtain the subjectivity score, calculated as the ratio between the number of subjective words in the text and the total number of words. To ensure comparability to the machine learning approach, we also construct the subjectivity score at the sentence level, calculated as the ratio between the number of subjective sentences in the text and the total number of sentences. Subjective sentences are defined as sentences that contain at least one word from the 'subjectivity' category. Subjective sentences generally refer to personal opinion, emotion, or judgment, whereas objective refer to factual information. The motivation stems from the fact that qualitative judgment plays an important role in assigning sovereign credit ratings and could potentially be more efficiently detected by analyzing subjectivity than simple negative/positive dichotomy. We define qualitative

Table 2 (*continued*).

	Obs	Mean	St. Dev.	Median	Min	Max
Moody's						
Credit rating	1580	13.123	5.260	12.000	1.000	21.000
GDP per capita	1580	17.750	20.929	7.913	0.379	120.449
Real GDP growth	1580	0.034	0.036	0.034	−0.151	0.345
Inflation	1580	0.051	0.065	0.033	−0.037	0.857
Current account/GDP	1580	−0.012	0.074	−0.015	−0.635	0.336
Trade/GDP	1580	0.915	0.632	0.762	0.207	4.426
External debt/GDP	1580	1.590	5.051	0.627	0.036	67.677
Economic development	1580	0.378	0.485	0.000	0.000	1.000
Default history	1580	0.164	0.370	0.000	0.000	1.000
Log of int. reserves	1580	9.698	1.809	9.756	4.967	15.169
Government debt/GDP	1580	0.539	0.352	0.453	0.001	2.371
Budget balance/GDP	1580	−0.023	0.041	−0.024	−0.320	0.187
Institutional quality	1580	14.169	4.120	13.500	6.000	22.000
Governance	1580	23.319	4.240	23.083	12.375	34.000
Trade proximity	1580	0.011	0.027	0.002	0.000	0.201
Common language	1580	0.209	0.407	0.000	0.000	1.000
Religious proximity	1580	0.529	0.237	0.636	0.011	0.805
Geographical distance	1580	78.661	35.002	73.424	0.000	163.711
Net sentiment (W, dict)	1580	−1.156	2.526	−0.870	−14.290	8.760
Negative sentiment	1580	4.146	1.947	4.050	0.000	14.290
Positive sentiment	1580	2.990	1.381	2.900	0.000	8.760
Polarity (W, dict)	1580	−0.138	0.349	−0.143	−1.000	1.000
Polarity (S, ML)	1580	0.286	0.457	0.363	−1.000	1.000
Subjectivity (W, dict)	1580	2.446	1.161	2.400	0.000	7.600
Subjectivity (S, dict)	1580	0.303	0.122	0.304	0.000	0.692
Subjectivity (S, ML)	1580	0.435	0.153	0.421	0.000	1.000

S&P: Country-year observations for 97 countries in the period from 2002 to 2018.
Fitch: Country-year observations for 98 countries in the period from 1999 to 2018.
Moody's: Country-year observations for 100 countries in the period from 1995 to 2018.

judgment of the rating committee as a subjective interpretation of soft information, which is unobservable and proxied by several indicators but may include potential bias as well. Cantor and Packer (1996) state that analysts may face several barriers when assessing a country's political and economic status, which is, as Luitel et al. (2016) point out, especially true for emerging markets, where the data is usually limited and/or of questionable quality. This leads to analysts having to rely more on their qualitative judgment for such countries compared to the advanced markets. The increased use of qualitative judgment of the rating committee may thus be reflected in a higher subjectivity score and vice versa.

The two final measures of sentiment and subjectivity that we employ are based on a machine-learning approach. The process involves several key steps. Initially, a portion of the complete text corpus is designated as the training set. Within this set, each sentence is manually categorized, with categories such as positive, negative, or other sentiments, as well as objective or subjective classifications. To prepare the data for analysis, we perform preprocessing tasks such as removing punctuation and numbers, tokenizing, filtering out stop words, and stemming. Next, we train a variety of sentiment analysis algorithms on the preprocessed training set. Our preferred algorithm is Naïve Bayes, a well-established method in text analysis. By utilizing the pre-classified data, this algorithm learns the rules or patterns for sentiment and subjectivity classification. These learned rules are then applied to the entire corpus to classify all the sentences. Based on these initial classifications or their combinations, we construct sentiment and subjectivity measures. The first measure is the polarity index, as previously defined. It calculates the count of positive sentences ($pos_{i,t}$) and negative sentences ($neg_{i,t}$) in the text. The second measure is subjectivity, which quantifies the ratio of subjective sentences to the total number of sentences. These measures, along with other variables, are utilized for further analysis. Table 2 presents the summary statistics for the textual analysis measures. Additionally, Table 3 displays the correlations between these measures. On average, sentiment or polarity exhibits a negative correlation with subjectivity measures.

3.2. Economic and cultural proximity

A fair body of existing literature argues that sovereign credit ratings are biased, as rating agencies favor their home countries or those close to them and disfavor emerging markets (Fuchs and Gehring, 2017; Zheng, 2012; De Moor et al., 2018). They claim this bias is substantial and mostly downward for emerging markets and upward for advanced countries. To control for potential bias, we include additional variables as proxies for economic and cultural proximity.

In relation to the economic proximity, Luitel et al. (2016) find evidence that US rating agencies favor countries that have stronger geopolitical and trade ties with the US. We thus construct a variable reflecting the trade intensity of a country with the US in line with De Moor et al. (2018). The rationale behind this is that a more intense trade between the US and the respective country would lead to higher sovereign credit ratings of the latter. The measure is constructed as:

$$Trade\ proximity_{i,t} = \frac{Imports_{USA,i,t} + Exports_{i,USA,t}}{Total\ trade_{USA,t}} \tag{2}$$

Table 3
Correlations between textual sentiment and subjectivity measures.

	(1)	(2)	(3)	(4)	(5)	(6)
S&P						
(1) Net sentiment (W, dict)	1.0000					
(2) Polarity (W, dict)	0.9552***	1.0000				
(3) Polarity (S, ML)	0.6883***	0.6731***	1.0000			
(4) Subjectivity (W, dict)	−0.1693***	−0.1822***	−0.2232***	1.0000		
(5) Subjectivity (S, dict)	−0.1443***	−0.1467***	−0.2117***	0.8683***	1.0000	
(6) Subjectivity (S, ML)	−0.0972***	−0.0555**	−0.1523***	0.2383***	0.3639***	1.0000
Fitch						
(1) Net sentiment (W, dict)	1.0000					
(2) Polarity (W, dict)	0.9503***	1.0000				
(3) Polarity (S, ML)	0.6034***	0.5869***	1.0000			
(4) Subjectivity (W, dict)	−0.1813***	−0.1902***	−0.2182***	1.0000		
(5) Subjectivity (S, dict)	−0.1684***	−0.1734***	−0.2348***	0.8543***	1.0000	
(6) Subjectivity (S, ML)	−0.1174***	−0.0670***	−0.2152***	0.2638***	0.3822***	1.0000
Moody's						
(1) Net sentiment (W, dict)	1.0000					
(2) Polarity (W, dict)	0.9226***	1.0000				
(3) Polarity (S, ML)	0.5822***	0.5909***	1.0000			
(4) Subjectivity (W, dict)	−0.2191***	−0.2132***	−0.3021***	1.0000		
(5) Subjectivity (S, dict)	−0.1708***	−0.1891***	−0.2636***	0.8493***	1.0000	
(6) Subjectivity (S, ML)	0.0220	0.0389	0.0246	−0.0031	0.1367***	1.0000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where $Imports_{USA,i,t}$ denotes the imports from country i to the USA in year t, $Exports_{i,USA,t}$ denotes the exports from the USA to country i in year t, and $Total\ trade_{USA,t}$ denotes the total imports to the USA and exports from the USA in year t.

Studies by Fuchs and Gehring (2017), Gültekin-Karakaş et al. (2011), Özturk (2014) and De Moor et al. (2018) also find evidence of cultural proximity bias. We thus include three cultural proximity variables: a dummy variable that equals 1 if English is the common official language, and zero otherwise, the probability that two randomly chosen individuals in the USA and particular country share the same religion, and geographical distance (in km) based on latitude and longitude from Washington DC (U.S.) to the capital city of a particular country. For religious proximity, we take into account four major religious groups: Christianity, Islam, Judaism, and others. The probability is then calculated using the following formula:

$$Religious\ proximity(r,s) = \sum_{w=1}^{4} p(r,w) \cdot p(s,w) \tag{3}$$

where $p(r,w)$ denotes the share of population in country r that identifies as belonging to religion w and $s = USA$.

3.3. Methodology

Sovereign credit ratings have an ordered structure by definition. Early studies on the determinants of sovereign credit ratings used linear estimation techniques (OLS). This approach is problematic because it ignores the ordered structure of the ratings and assumes the distances between credit rating classes are equal (i.e., the transition from AAA/Aaa to AA+/Aa1 is treated equally as the transition from BBB-/Baa3 - investment grade to BB+/Ba1 - speculative grade). This problem can be avoided by using ordered response models (Reusens and Croux, 2017; Afonso et al., 2011; Mora, 2006; Bissoondoyal-Bheenick, 2005).

Subsequent studies predominantly applied either ordered response models (Özturk, 2014; Mellios and Paget-Blanc, 2006; Bissoondoyal-Bheenick, 2005; Hu et al., 2002), or both fixed and/or random effects estimation and ordered response models (Erdem and Varli, 2014; Afonso et al., 2011). We use an ordered logit with random effects[15] that takes into account both the panel structure of the dataset and the ordered nature of sovereign credit ratings (Erdem and Varli, 2014; Afonso et al., 2011, 2009; Agresti and Natarajan, 2001).

We estimate the following model:

$$y_{it}^* = \alpha_i + \beta' x_{it} + \varepsilon_{it} \tag{4}$$

[15] We chose random effects because no consistent estimator for an ordered logit (or probit) with fixed effects that can explicitly include individual fixed effects is available. Consequently, various estimation approaches were proposed in the literature but offered little guidance on when to use which estimator (Riedl and Geishecker, 2014).

where y^*_{it} is the unobserved latent variable. The final rating is then given by several cut-off points:

$$y_{it} = \begin{cases} Aaa & \text{if} \quad y^*_{it} > c_{20} \\ Aa1 & \text{if} \quad c_{20} > y^*_{it} > c_{19} \\ \quad \vdots & \\ C & \text{if} \quad c_1 > y^*_{it} \end{cases} \tag{5}$$

The parameters in Eq. (3) and cut-off points in (4) are estimated using maximum likelihood. By using the ordered logit with random effects we assume both errors ε_i and μ_{it} are normally distributed (Wooldridge, 2002).

4. Results

We begin with a bivariate analysis of our key variables, namely net sentiment and subjectivity measures. The observations are pooled for all three agencies, where the value for each observation is averaged between the three agencies' credit action reports measures. We compare the means of advanced countries and emerging markets and test the differences in means. The results are reported in Panel A of Table 4. We find statistically significant differences in means for both sentiment and subjectivity measures between advanced and emerging economies. Specifically, the average net sentiment in sovereign credit reports for emerging markets is −1.63%, while the average net sentiment for advanced economies is −1.41%. Both polarity measures are also significantly higher for emerging markets. As expected, this indicates that general perception is more strongly expressed in the reports of emerging markets compared to advanced economies. On the other hand, we expected higher subjectivity scores for emerging markets due to data shortage and, consequently, an increased emphasis on qualitative judgment. This is true only for the subjectivity measure from the machine learning approach.

We repeat the analysis separately for individual credit rating agencies. The results are presented in the Appendix in Tables A.12, A.13, and A.14. The individual results confirm the significant differences in means of sentiment measures, but the results for subjectivity measures are contradictory. None of the differences in means of S&P subjectivity measures are significant. Only the differences in means of sentence level subjectivity measures are significant for Fitch, and the difference in means of word level subjectivity measure for Moody's. We explore the differences between groups of countries further in Section 2.5.2.

We also compare the means of key variables before and after the 2008 Global financial crisis and report the results in Panel B of Table 4. As expected, we detect a significant difference in sentiment and subjectivity scores. Sentiment measures were higher before the crisis. Specifically, the average net sentiment before the crisis was higher (−1.27%) than after the crisis (−1.58%). This corresponds to a lower average negative sentiment and a higher average positive sentiment before the crisis compared to after the crisis. The average subjectivity scores from the dictionary-based approach are higher after the crisis, e.g., at 3.00% (word level), compared to before the crisis, at 2.15% (word level), reflecting the increased demand for transparency of credit rating agencies' methodologies after the crisis. Focusing on individual agencies, the results for Fitch and Moody's confirm the pooled results, whereas the results for S&P are either statistically insignificant or negligible for sentiment measures. We additionally investigate the relationships before and after the crisis in Section 2.5.3.

Finally, we combine both approaches and compare the means of emerging markets and advanced economies before and after the crisis. The results are shown in Panels C, D, E, and F of Table 4 and are comparable to the overall sample results in Panels A and B. The most notable result is that textual sentiment measures for emerging markets changed less after the global financial crisis compared to advanced economies (Panels C and D). Another interesting finding is that the difference in average net sentiment between emerging and advanced economies decreased after the crisis (Panels E and F). Similarly, the difference in average subjectivity from the dictionary-based approach between emerging and advanced economies is not statistically significant before the crisis but is significant after the crisis (Panels E and F). We observe the opposite for subjectivity from the machine learning approach. The latter also supports our argument of the increased transparency of credit rating agencies after the crisis, who were forced to present a more realistic picture of the advanced economies. For example, Gaillard (2012) argues that, prior to the European debt crisis, credit rating agencies attached too much weight to both the advanced economy status as well as the eurozone membership of Greece. We continue with the overall sample analysis in the next section before taking a closer look at the two country subgroups and subperiods in the subsequent two sections.

4.1. Overall sample results

We extend the bivariate comparison to a multivariate analysis by exploring three baseline models. The first model (Model 1) contains only the variables that are considered the hard information, i.e. macroeconomic and fiscal strength variables defined in Table 1. Taking the methodologies (Standard & Poor's, 2017; Fitch, 2017; Moody's, 2016) and previous findings (Özturk, 2014; Butler and Fauver, 2006) into account, it is evident that soft information plays an important role when assigning sovereign credit ratings. Model 2 is, therefore, an extension of Model 1 with proxies for institutional strength and political risk. To control for a potential bias identified in prior literature (Fuchs and Gehring, 2017; Luitel et al., 2016; Zheng, 2012) we include proxies for cultural and economic proximity in Model 3.[16] The results are presented in Table 5.

[16] We also estimate Model 1 extended with proxies for bias. The results are comparable to the results of Model 1 and are available upon request.

Table 4
Bivariate pooled analysis: mean comparison of key variables for advanced economies (AE) and emerging markets (EME), and before and after the Global financial crisis (GFC).

	(1)	(2)	(3)	(4)	(5)	(6)
	A: Emerging markets vs. advanced economies					
Mean (EME)	−1.634	−0.200	0.306	2.605	0.325	0.392
Mean (AE)	−1.141	−0.143	0.426	2.775	0.336	0.375
Diff. in means (EME-AE)	−0.493***	−0.057***	−0.120***	−0.170***	−0.010**	0.017***
	(0.091)	(0.012)	(0.015)	(0.044)	(0.005)	(0.005)
Observations (EME)	1071	Observations (Total)			1669	
Observations (AE)	598					
	B: Before vs. after the Global financial crisis (GFC)					
Mean (before GFC)	−1.273	−0.150	0.393	2.154	0.289	0.413
Mean (after GFC)	−1.577	−0.199	0.321	2.997	0.355	0.368
Diff. in means (before-after GFC)	0.304***	0.049***	0.072***	−0.843***	−0.065***	0.045***
	(0.101)	(0.013)	(0.016)	(0.039)	(0.005)	(0.005)
Observations (before GFC)	656	Observations (Total)			1669	
Observations (after GFC)	1013					
	C: Emerging markets before vs. after the Global financial crisis					
Mean (before GFC)	−1.486	−0.175	0.319	2.137	0.289	0.423
Mean (after GFC)	−1.736	−0.218	0.297	2.932	0.351	0.370
Diff. in means (before-after GFC)	0.250*	0.043**	0.022	−0.795***	−0.062***	0.053***
	(0.133)	(0.017)	(0.021)	(0.050)	(0.006)	(0.007)
Observations (before GFC)	440	Observations (Total EME)			1071	
Observations (after GFC)	631					
	D: Advanced economies before vs. after the Global financial crisis					
Mean (before GFC)	−0.837	−0.099	0.543	2.191	0.291	0.392
Mean (after GFC)	−1.313	−0.168	0.360	3.105	0.361	0.365
Diff. in means (before-after GFC)	0.475***	0.069***	0.182***	−0.914***	−0.070***	0.027***
	(0.138)	(0.018)	(0.022)	(0.062)	(0.007)	(0.007)
Observations (before GFC)	216	Observations (Total AE)			598	
Observations (after GFC)	382					
	E: Emerging vs. advanced markets before the Global financial crisis					
Mean (EME)	−1.486	−0.175	0.319	2.137	0.289	0.423
Mean (AE)	−0.837	−0.099	0.543	2.191	0.291	0.392
Diff. in means (EME-AE)	−0.649***	−0.076***	−0.223***	−0.054	−0.002	0.031***
	(0.158)	(0.020)	(0.024)	(0.065)	(0.008)	(0.009)
Observations (EME)	440	Observations (Total before GFC)			656	
Observations (AE)	216					
	F: Emerging vs. advanced markets after the Global financial crisis					
Mean (EME)	−1.736	−0.218	0.297	2.932	0.351	0.370
Mean (AE)	−1.313	−0.168	0.360	3.105	0.361	0.365
Diff. in means (EME-AE)	−0.424***	−0.050***	−0.063***	−0.173***	−0.010**	0.005
	(0.108)	(0.014)	(0.018)	(0.046)	(0.004)	(0.005)
Observations (EME)	631	Observations (Total after GFC)			1013	
Observations (AE)	382					

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict), (5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Model 1, GDP per capita, inflation, current account, economic development, default history, and government debt seem to have a significant effect on sovereign credit ratings for all three agencies. Additionally, external debt significantly explains part of the variability of Fitch's credit sovereign ratings, while international reserves play a significant role for ratings by Fitch and Moody's. The signs are as expected and found in earlier research. We find that sovereign credit ratings can, to some extent, be described by just a handful of variables. This is in line with previous research, including Cantor and Packer (1996), Afonso (2003), and Hill et al. (2010). After adding proxies for soft information in Model 2, inflation becomes insignificant for Moody's, whereas international reserves now have explanatory power for all three agencies. Out of the newly added variables, namely institutional quality and governance, only the latter adds to the explanation of variability in sovereign credit ratings. When controlling for potential bias in Model 3, none but trade proximity are significant. Thus, there does not seem to be any evidence of cultural proximity bias, but the

Table 5
Estimation results of the ordered logit with random effects for the determinants of sovereign credit ratings.

	Sovereign credit ratings								
	Model 1			Model 2			Model 3		
	S&P	Fitch	Moody's	S&P	Fitch	Moody's	S&P	Fitch	Moody's
GDP per capita	0.150***	0.159***	0.121**	0.171***	0.188***	0.150***	0.182***	0.196***	0.161***
	(0.054)	(0.051)	(0.047)	(0.053)	(0.054)	(0.049)	(0.054)	(0.055)	(0.051)
Real GDP growth	3.879	−0.099	0.198	0.677	−2.478	−1.683	0.517	−2.729	−1.894
	(3.704)	(2.818)	(2.389)	(3.718)	(3.168)	(2.247)	(3.760)	(3.206)	(2.250)
Inflation	−7.559***	−7.173***	−4.482*	−7.376***	−5.668**	−2.783	−7.163***	−5.809**	−2.950
	(2.624)	(2.433)	(2.296)	(2.054)	(2.412)	(2.382)	(2.093)	(2.371)	(2.435)
Current account/GDP	−5.899***	−4.348**	−6.067***	−4.819**	−3.740***	−4.552**	−4.877**	−3.777***	−4.753**
	(2.226)	(2.054)	(2.170)	(2.163)	(1.437)	(2.097)	(2.068)	(1.415)	(2.046)
Trade/GDP	0.420	0.316	−0.448	1.083	0.878	−0.120	1.222*	0.987	−0.134
	(0.853)	(0.722)	(0.676)	(0.764)	(0.701)	(0.598)	(0.730)	(0.679)	(0.610)
External debt/GDP	−0.019	−0.191**	−0.138	0.002	−0.180**	−0.124	−0.008	−0.184**	−0.130*
	(0.130)	(0.080)	(0.088)	(0.139)	(0.076)	(0.076)	(0.148)	(0.073)	(0.074)
Economic development	10.199***	10.498***	8.772***	6.289***	7.512***	5.609***	5.684***	7.100***	5.487***
	(2.065)	(1.643)	(1.678)	(1.936)	(1.768)	(1.665)	(1.944)	(1.788)	(1.689)
Default history	−3.881***	−5.917***	−6.187***	−3.292***	−5.248***	−5.654***	−3.102***	−5.226***	−5.554***
	(1.198)	(1.106)	(1.216)	(0.992)	(1.017)	(1.228)	(0.953)	(1.007)	(1.225)
Log of int. reserves	0.444	0.468*	0.392*	0.795**	0.661**	0.598***	0.615*	0.555**	0.461**
	(0.315)	(0.253)	(0.208)	(0.350)	(0.265)	(0.198)	(0.355)	(0.255)	(0.194)
Government debt/GDP	−9.921***	−10.017***	−8.691***	−7.923***	−8.276***	−7.118***	−8.142***	−8.407***	−7.360***
	(1.504)	(1.236)	(1.284)	(1.211)	(1.079)	(1.133)	(1.267)	(1.079)	(1.157)
Budget balance/GDP	−0.107	−0.875	−0.675	−3.896	−5.031	−5.380	−4.385	−5.359	−5.439
	(3.609)	(3.586)	(3.712)	(3.353)	(3.292)	(3.364)	(3.320)	(3.273)	(3.360)
Institutional quality				0.069	−0.025	−0.001	0.110	−0.023	−0.012
				(0.160)	(0.134)	(0.102)	(0.160)	(0.131)	(0.103)
Governance				0.469***	0.445***	0.430***	0.468***	0.452***	0.427***
				(0.063)	(0.061)	(0.051)	(0.061)	(0.060)	(0.052)
Trade proximity							68.756***	31.837***	31.604***
							(22.090)	(10.155)	(8.951)
Common language							−0.654	−1.150	−0.360
							(0.812)	(0.845)	(0.686)
Religious proximity							1.460	−0.892	0.745
							(1.713)	(1.574)	(1.394)
Geographical distance							0.011	−0.009	0.012
							(0.010)	(0.012)	(0.010)
Observations	1382	1433	1580	1382	1433	1580	1382	1433	1580

Standard errors in parentheses. Cut-off estimates are not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

results suggest there is some economic proximity bias present in sovereign credit ratings. Contradictorily, De Moor et al. (2018), Luitel et al. (2016) and Fuchs and Gehring (2017) detect the presence of both types of bias.

Next, we repeat the analysis after separately[17] adding indicators for (textual) sentiment and subjectivity to each of the three models. The results are shown in Table 6. Overall, sentiment and subjectivity measures have explanatory power in Model 1. This is consistent with Agarwal et al. (2019), who also include sentiment in the analysis of CDS spreads and future downgrades but do not introduce proxies for soft information and bias and conclude that negative sentiment contains important information beyond credit ratings alone.

While sentiment measures from the dictionary-based approach become insignificant in Models 2 and 3, sentiment from the machine learning approach does not. This result suggests that soft information is (to some extent) reflected in credit action reports via (textual) sentiment, which helps explain sovereign credit ratings if proxies for soft information are not included in the model. Additionally, the proxy for economic proximity bias remains significant in Model 3, and the coefficients are comparable (see Tables A.15–A.17 in the Appendix). Subjectivity is statistically significant (albeit marginally) in all three models for Moody's, which suggests there is some evidence of the credit rating committee's qualitative judgment being expressed in the reports and having

[17] We also include indicators for sentiment and subjectivity indicators simultaneously in all models. The results are comparable and available upon request.

Table 6
Estimation results with sentiment and subjectivity scores of the ordered logit with random effects for the determinants of sovereign credit ratings.

	Sovereign credit ratings				
	S&P	S&P (Full Reports)	Fitch	Fitch (Full Reports)	Moody's
	Model 1				
Net sentiment (W, dict)	0.052	0.313***	0.080*	0.280**	0.121***
	(0.042)	(0.108)	(0.041)	(0.128)	(0.037)
Polarity (W, dict)	0.760***	2.663***	0.525	1.280*	0.799***
	(0.293)	(0.739)	(0.349)	(0.706)	(0.279)
Polarity (S, ML)	1.362***	5.632***	1.311***	2.962***	0.711***
	(0.293)	(1.063)	(0.333)	(0.787)	(0.192)
Subjectivity (W, dict)	−0.152*	−0.242	−0.098	−0.206	−0.327***
	(0.080)	(0.275)	(0.093)	(0.189)	(0.088)
Subjectivity (S, dict)	−1.218	−3.265	−1.253*	−2.516*	−2.305***
	(0.747)	(2.661)	(0.759)	(1.438)	(0.758)
Subjectivity (S, ML)	1.513*	−2.727	−0.422	−1.178	−0.251
	(0.816)	(2.514)	(0.576)	(2.007)	(0.631)
	Model 2				
Net sentiment (W, dict)	0.033	0.266**	0.025	0.119	0.044
	(0.048)	(0.104)	(0.042)	(0.129)	(0.037)
Polarity (W, dict)	0.492	2.081***	0.055	0.349	0.214
	(0.344)	(0.761)	(0.367)	(0.673)	(0.284)
Polarity (S, ML)	1.042***	4.764***	1.004***	1.963***	0.355*
	(0.323)	(0.998)	(0.311)	(0.743)	(0.210)
Subjectivity (W, dict)	−0.042	0.013	0.050	−0.003	−0.192**
	(0.085)	(0.268)	(0.087)	(0.192)	(0.090)
Subjectivity (S, dict)	−0.537	−1.561	−0.550	−1.589	−1.309*
	(0.735)	(2.572)	(0.688)	(1.365)	(0.756)
Subjectivity (S, ML)	0.707	−2.891	−0.233	−0.984	−0.739
	(0.720)	(2.246)	(0.597)	(2.089)	(0.665)
	Model 3				
Net sentiment (W, dict)	0.033	0.232**	0.021	0.094	0.043
	(0.048)	(0.105)	(0.043)	(0.128)	(0.037)
Polarity (W, dict)	0.458	1.828**	0.042	0.212	0.214
	(0.347)	(0.765)	(0.370)	(0.666)	(0.285)
Polarity (S, ML)	1.024***	4.684***	1.010***	1.854**	0.325
	(0.324)	(1.016)	(0.310)	(0.767)	(0.207)
Subjectivity (W, dict)	−0.023	0.061	0.058	0.000	−0.198**
	(0.087)	(0.261)	(0.086)	(0.193)	(0.091)
Subjectivity (S, dict)	−0.365	−0.944	−0.473	−1.384	−1.301*
	(0.733)	(2.476)	(0.686)	(1.379)	(0.774)
Subjectivity (S, ML)	0.766	−2.901	−0.228	−0.952	−0.810
	(0.720)	(2.251)	(0.602)	(2.128)	(0.673)
Observations	1382	1422	1433	1232	1580

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

explanatory power beyond the included proxies for soft information and potential bias. However, results for S&P and Fitch do not confirm these findings. As a robustness check, we also estimate Model 3 using fixed effects, random effects, pooled OLS, and ordinal logit, which are common estimation techniques in prior literature. The results are reported in the Appendix in Table A.18 and generally support our main conclusions.

We then examine the accuracy of correct predictions and predictions within one, two, and three notches for the three baseline models and their extensions with sentiment and subjectivity measures. The results are presented in Table 7. Overall, Moody's correct predictions outperform correct predictions for S&P and Fitch. While predictions within one notch are comparable between all three agencies, predictions within two and three notches for S&P and Fitch exceed those of Moody's. By comparing the three baseline models, it is evident that adding soft information variables, specifically political risk, and institutional strength variables, greatly improves the accuracy of predictions. The change in correct predictions is comparable for the three agencies, with increases ranging between 7.12 percentage points for Fitch and 7.89 percentage points for S&P. Predictions within three notches for S&P, Fitch and

Table 7
Predictions of estimated models in %.

	% predicted within n notches											
	S&P				Fitch				Moody's			
	n = 0	n = 1	n = 2	n = 3	n = 0	n = 1	n = 2	n = 3	n = 0	n = 1	n = 2	n = 3
	Model 1											
No textual indicators	22.65	48.91	72.43	85.60	22.82	47.66	70.83	85.62	28.42	49.30	66.46	78.48
Net sentiment (W, dict)	22.29	48.26	72.00	85.31	23.24	48.01	71.11	85.90	27.97	50.13	67.41	79.05
Polarity (W, dict)	22.29	47.97	71.85	85.17	23.03	48.22	71.11	85.97	27.78	49.81	67.47	78.92
Polarity (S, ML)	22.29	48.26	72.79	85.17	24.35	48.78	71.60	86.04	28.42	49.81	67.15	78.99
Subjectivity (W, dict)	22.50	49.06	72.94	86.03	23.73	48.50	71.60	86.11	29.30	50.76	68.54	81.08
Subjectivity (S, dict)	22.36	48.99	72.65	85.75	23.59	48.36	71.39	86.39	29.18	49.87	67.41	79.30
Subjectivity (S, ML)	23.23	49.06	72.87	86.11	22.89	47.52	70.76	85.55	28.35	49.11	66.39	78.42
	Model 2											
No textual indicators	30.54	64.11	86.11	94.50	29.94	59.32	82.97	93.44	35.95	62.15	79.87	90.63
Net sentiment (W, dict)	30.75	63.60	85.96	94.50	29.94	59.04	82.69	93.37	35.25	61.71	79.75	90.57
Polarity (W, dict)	30.10	63.53	85.96	94.57	30.08	59.39	82.97	93.44	35.57	61.90	79.68	90.70
Polarity (S, ML)	31.04	62.81	85.75	94.43	29.24	59.53	82.83	93.09	35.89	61.65	79.81	90.82
Subjectivity (W, dict)	30.39	64.11	86.18	94.50	29.52	59.11	82.76	93.37	36.27	62.78	80.06	90.89
Subjectivity (S, dict)	30.10	63.97	86.25	94.50	29.73	59.39	82.97	93.51	35.51	62.22	79.43	90.82
Subjectivity (S, ML)	30.32	63.82	86.25	94.50	29.94	59.25	82.90	93.44	34.87	60.82	79.11	90.63
	Model 3											
No textual indicators	32.20	64.83	86.32	94.65	30.15	60.50	83.53	94.28	34.75	62.28	80.13	91.33
Net sentiment (W, dict)	31.84	64.54	86.18	94.57	29.80	60.36	83.32	94.35	34.68	61.77	79.81	91.33
Polarity (W, dict)	31.62	64.47	85.89	94.65	30.29	60.43	83.46	94.28	34.62	62.03	79.94	91.27
Polarity (S, ML)	32.42	64.69	85.96	94.50	29.52	60.92	83.74	94.28	35.25	61.96	80.00	91.14
Subjectivity (W, dict)	32.20	64.69	86.40	94.57	29.87	60.50	83.46	94.21	35.38	61.71	80.95	91.71
Subjectivity (S, dict)	32.20	64.62	86.25	94.50	30.01	60.57	83.46	94.49	35.32	61.96	80.19	91.46
Subjectivity (S, ML)	32.13	64.91	86.25	94.72	30.29	60.50	83.32	94.14	35.25	61.96	79.56	91.27

Moody's increase by 8.90, 7.82 and 12.15 percentage points, respectively. Adding the proxies for potential bias only marginally improves the results, most notably correct predictions for S&P, which increase to 32.20%. The results are comparable to Reusens and Croux (2017), who estimate a multi-year ordered probit without proxies for soft information and achieve 28% correctly predicted ratings. Özturk (2014) also applies ordered response models and is able to correctly predict 29.42% of ratings while separately including proxies for governance to the model improves the predictions to between 31.61% and 42.47%.

Adding sentiment measures to the three models improves the accuracy of predictions to a certain extent for Model 1, most notably for Fitch, which increases to between 23.03% and 24.35%. This is in line with our previous finding that sentiment partly reflects soft information as expressed in the reports but loses explanatory power when proxies for soft information are added to the model. Consequently, the predictions of Models 2 and 3 with sentiment are comparable to predictions without sentiment, which may be due to the correlation between soft information and sentiment. Similarly, subjectivity measures only slightly affect the accuracy of predictions. The most notable difference is in Model 1 for Fitch, where the percent of accurately predicted sovereign credit ratings increases from 22.82% to 24.35% when including polarity at the sentence level. The best model in terms of correct predictions seems to be Model 3 with polarity from the machine learning approach for S&P (32.42%), Model 3 with polarity from the dictionary-based approach and with subjectivity from the machine learning approach for Fitch (30.29%), and Model 2 with subjectivity from the dictionary-based approach at word level for Moody's (36.27%).

The highest accuracy within three notches is shared by Models 3 with and without polarity from the dictionary-based approach for S&P (94.65%), Model 3 with subjectivity from the dictionary-based approach at sentence level for Fitch (94.49%), and Model 3 with subjectivity from the dictionary-based approach at word level for Moody's (91.71%).

4.2. Advanced economies vs. emerging markets

Given the existing evidence that credit rating agencies unjustifiably assign lower ratings to emerging countries compared to advanced markets (De Moor et al., 2018), we analyze the potential discrepancies in sentiment and subjectivity scores between these groups of countries. We introduce an interaction of economic development with sentiment and subjectivity measures, respectively.[18] The results are presented in Table 8. The coefficients for sentiment and subjectivity measures correspond to emerging markets, while the interaction is the difference in coefficients between emerging and advanced markets. We focus on the rating action reports by the three agencies, which are directly comparable, but also show the results for full rating reports by S&P and Fitch.

[18] We also examine interaction with investment grade vs. speculative grade, OECD member vs. non-member, and previously defaulted vs. never defaulted. The results are comparable and available upon request.

Interaction terms with sentiment measures are predominantly insignificant, indicating there are negligible differences in measured textual sentiment between both groups of countries. We detect significant differences only for Moody's. These differences remain significant even after expanding the model with proxies for political risk and potential bias, suggesting there is additional information in textual sentiment regarding discrepancies between emerging and advanced markets. This could most likely mean the difference in the general perception of the two groups of countries, but could also mean either additional soft information not captured by institutional quality and governance or bias we have not controlled for. Interaction with subjectivity measures is generally statistically insignificant for S&P and Fitch but statistically significant for Moody's, which is partially in contradiction with our initial results in Panel A of Tables A.12–A.14. Interestingly, while there is little evidence of differences in rating action reports by S&P and Fitch, these differences are significant in the full credit rating reports. The detailed analysis suggests that the rating committees of all three agencies apply different degrees of qualitative judgment to advanced economies and emerging markets, which is in line with the initial hypothesis. The negative signs of the interaction terms suggest a stronger effect of subjectivity measures of advanced economies compared to emerging markets.

We also run separate regressions for advanced economies and emerging markets of Model 3 with sentiment and subjectivity measures. The results without textual sentiment measures are reported in the Appendix in Table A.19, while Table A.20 shows the results for sentiment and subjectivity measures, respectively. Even though the coefficients are predominantly statistically insignificant, the differences in coefficients for sentiment and subjectivity measures between advanced and emerging markets are noticeable. Furthermore, different determinants seem to be influencing the sovereign credit ratings of advanced economies and emerging markets. Most notably, trade and religious proximity appear to have explanatory power for advanced economies. The latter, which has a positive sign, suggests there is some evidence that sovereign credit ratings are culturally biased upward for advanced markets. This is consistent with Gültekin-Karakaş et al. (2011), who note that high-income countries are rated higher than low-income countries, ceteris paribus. On the other hand, GDP per capita, default history, and trade proximity significantly affect the sovereign credit ratings of emerging markets, where the latter points to a positive economic bias toward emerging markets. Additionally, we observe substantial differences in coefficients among the significant determinants for both groups of countries (e.g., inflation, government debt) or even opposite signs (e.g., international reserves). This may be evidence of different weighting schemes applied by the credit rating committee. According to Fuchs and Gehring (2017) and Zheng (2012), the degree of foreign bias in sovereign ratings varies across agencies due to different weights being applied to the qualitative judgment.

4.3. Global financial crisis

Additionally, we also examine the behavior of sentiment and subjectivity measures before and after the 2008 global financial crisis. We introduce an interaction of the global financial crisis dummy (1 if the year of observation is 2008 or later, 0 otherwise) with sentiment and subjectivity measures.[19] The results are presented in Table 9. The coefficients for sentiment and subjectivity measures correspond to the period before the global crisis, while the interaction is the difference in coefficients between before and after the crisis. As expected, the difference in sentiment measures is significant in all three models, corresponding to the general negative financial climate after the crisis. However, the differences in subjectivity measures, apart from the measure from the machine learning approach, are not statistically significant, which is in contradiction with our initial results in Panel B of Table 4. The further analysis thus indicates that the global crisis did not cause a disruption in the way the rating committee employs qualitative judgment.

4.4. Determinants of sentiment and subjectivity

As the last step, we regress sentiment and subjectivity measures on proxies for soft information and potential bias. We use random effects. The results are presented in Table 10 and are in line with our previous findings. Sentiment measures are explained by institutional quality, governance, trade proximity, and geographical distance. The R^2 are comparable and range between 0.10 and 0.15. On the other hand, we were unable to explain much of the variability in subjectivity measures using the same explanatory variables. Only governance is significant for all three measures, and R^2 are relatively low, ranging between 0.02 and 0.03. We can conclude that sentiment, to a limited degree, captures soft information and potential bias, while subjectivity reflects the qualitative judgment of the rating committee and thus offers some additional information not captured by the determinants of sovereign credit ratings.

Additionally, we also repeat the analysis by using the subcomponents of institutional quality and governance. Institutional quality comprises law and order, bureaucracy quality, democratic accountability and corruption, and governance includes government stability, socio-economic conditions, and investment profile. The results are reported in the Appendix in Table A.21. Sentiment measures are predominantly explained by the subcomponents of governance, while only the bureaucracy quality and law and order subcomponents of institutional quality are statistically significant. Similarly, the subcomponents of governance and law and order are statistically significant when trying to explain subjectivity measures.

[19] We also analyze interaction with systemic banking crisis dummy (Laeven and Valencia, 2018), and interaction with the crisis starting in 2010. The results are comparable and available upon request.

Table 8
Estimation results of sentiment and subjectivity scores from the ordered logit with random effects for the determinants of sovereign credit ratings, including interaction with economic development.

	Sovereign credit ratings				
	S&P	S&P (Full Reports)	Fitch	Fitch (Full Reports)	Moody's
	Model 1				
ED = 1 ×Net sentiment (W, dict)	0.081	0.039	0.076	0.251	0.212**
	(0.123)	(0.382)	(0.082)	(0.284)	(0.082)
ED = 1 ×Polarity (W, dict)	0.794	1.806	0.961	3.102**	1.806***
	(0.821)	(2.368)	(0.690)	(1.523)	(0.633)
ED = 1 ×Polarity (S, ML)	−0.169	0.402	0.818	3.921*	1.229**
	(0.780)	(2.701)	(0.651)	(2.227)	(0.510)
ED = 1 ×Subjectivity (W, dict)	−0.350**	−1.228***	−0.339*	−1.357***	−0.466**
	(0.160)	(0.451)	(0.199)	(0.491)	(0.214)
ED = 1 ×Subjectivity (S, dict)	−2.874*	−16.106***	−3.876**	−14.651***	−3.696**
	(1.626)	(5.028)	(1.809)	(3.965)	(1.629)
ED = 1 ×Subjectivity (S, ML)	−0.542	−16.787***	0.468	−7.488	2.269
	(2.060)	(5.215)	(1.331)	(5.600)	(1.474)
	Model 2				
ED = 1 ×Net sentiment (W, dict)	0.074	0.156	0.032	0.023	0.190**
	(0.144)	(0.337)	(0.100)	(0.340)	(0.081)
ED = 1 ×Polarity (W, dict)	0.738	2.079	0.492	1.781	1.543**
	(0.975)	(2.318)	(0.832)	(1.781)	(0.624)
ED = 1 ×Polarity (S, ML)	−0.397	0.543	0.407	2.214	1.441***
	(0.884)	(2.534)	(0.622)	(2.132)	(0.475)
ED = 1 ×Subjectivity (W, dict)	−0.310*	−1.205***	−0.231	−1.539***	−0.537***
	(0.171)	(0.429)	(0.189)	(0.478)	(0.198)
ED = 1 ×Subjectivity (S, dict)	−1.707	−15.203***	−3.064*	−16.755***	−4.471***
	(1.554)	(4.525)	(1.590)	(3.701)	(1.533)
ED = 1 ×Subjectivity (S, ML)	0.376	−14.749***	0.744	−5.381	2.770**
	(1.859)	(4.563)	(1.363)	(5.192)	(1.386)
	Model 3				
ED = 1 ×Net sentiment (W, dict)	0.083	0.126	0.038	0.110	0.198**
	(0.144)	(0.352)	(0.100)	(0.335)	(0.082)
ED = 1 ×Polarity (W, dict)	0.806	1.879	0.520	2.252	1.590**
	(0.975)	(2.423)	(0.836)	(1.751)	(0.625)
ED = 1 ×Polarity (S, ML)	−0.359	0.318	0.407	2.271	1.435***
	(0.878)	(2.578)	(0.610)	(2.098)	(0.472)
ED = 1 ×Subjectivity (W, dict)	−0.304*	−1.177***	−0.215	−1.478***	−0.516***
	(0.172)	(0.431)	(0.191)	(0.465)	(0.199)
ED = 1 ×Subjectivity (S, dict)	−1.744	−15.071***	−3.030*	−16.384***	−4.511***
	(1.554)	(4.525)	(1.604)	(3.548)	(1.550)
ED = 1 ×Subjectivity (S, ML)	0.165	−14.180***	0.709	−4.991	2.695*
	(1.868)	(4.618)	(1.379)	(5.085)	(1.394)
Observations	1382	1422	1433	1232	1580

ED = Dummy variable for Economic development.
Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusion

We apply a novel approach to analyzing the determinants of sovereign credit ratings by extending the traditional regression-based methodology with new measures (i.e., sentiment and subjectivity indicators) obtained through textual analysis of sovereign credit rating reports of rating agencies. There is substantial evidence regarding the impact of sentiment or tone (qualitative information) in corporate credit rating reports on corporate equity valuation (Loughran and McDonald, 2016; Kearney and Liu, 2014; Agarwal et al., 2016), but the evidence on the impact of sovereign credit rating reports on, e.g., the sovereign debt market is practically non-existent. Sovereign credit ratings can have economically more important consequences than firm-level credit ratings since they

Table 9
Estimation results of sentiment and subjectivity scores from the ordered logit with random effects for the determinants of sovereign credit ratings, including interaction with global crisis dummy.

	Sovereign credit ratings				
	S&P	S&P (Full Reports)	Fitch	Fitch (Full Reports)	Moody's
	Model 1				
GFC = 1 ×Net sentiment (W, dict)	0.187**	0.491***	0.229***	0.367*	0.258***
	(0.084)	(0.174)	(0.053)	(0.218)	(0.054)
GFC = 1 ×Polarity (W, dict)	1.510**	4.049***	1.876***	1.772	1.791***
	(0.693)	(1.439)	(0.445)	(1.251)	(0.417)
GFC = 1 ×Polarity (S, ML)	2.327***	4.946***	2.091***	4.194***	1.884***
	(0.608)	(1.535)	(0.486)	(1.443)	(0.405)
GFC = 1 ×Subjectivity (W, dict)	0.230	−0.069	0.018	−0.249	−0.125
	(0.144)	(0.368)	(0.136)	(0.379)	(0.168)
GFC = 1 ×Subjectivity (S, dict)	0.787	−1.286	0.774	1.070	−1.654
	(1.350)	(3.656)	(1.284)	(3.235)	(1.623)
GFC = 1 ×Subjectivity (S, ML)	−2.982	−7.426*	2.441**	−0.926	−0.310
	(1.910)	(4.124)	(1.193)	(3.864)	(1.143)
	Model 2				
GFC = 1 ×Net sentiment (W, dict)	0.187**	0.652***	0.224***	0.353*	0.210***
	(0.078)	(0.161)	(0.050)	(0.214)	(0.056)
GFC = 1 ×Polarity (W, dict)	1.475**	4.883***	1.862***	1.738	1.426***
	(0.629)	(1.380)	(0.426)	(1.242)	(0.438)
GFC = 1 ×Polarity (S, ML)	2.496***	6.074***	1.768***	4.278***	1.792***
	(0.619)	(1.334)	(0.499)	(1.489)	(0.390)
GFC = 1 ×Subjectivity (W, dict)	0.250*	0.151	0.161	−0.168	−0.168
	(0.150)	(0.379)	(0.145)	(0.418)	(0.159)
GFC = 1 ×Subjectivity (S, dict)	0.655	0.552	1.657	2.504	−1.839
	(1.364)	(3.861)	(1.313)	(3.665)	(1.551)
GFC = 1 ×Subjectivity (S, ML)	−3.768**	−5.940	2.916**	0.965	−0.806
	(1.777)	(3.802)	(1.147)	(3.828)	(1.121)
	Model 3				
GFC = 1 ×Net sentiment (W, dict)	0.168**	0.611***	0.229***	0.361*	0.197***
	(0.076)	(0.156)	(0.052)	(0.210)	(0.055)
GFC = 1 ×Polarity (W, dict)	1.310**	4.598***	1.887***	1.816	1.343***
	(0.605)	(1.342)	(0.441)	(1.215)	(0.436)
GFC = 1 ×Polarity (S, ML)	2.374***	5.932***	1.772***	4.192***	1.737***
	(0.619)	(1.290)	(0.506)	(1.483)	(0.379)
GFC = 1 ×Subjectivity (W, dict)	0.228	0.067	0.144	−0.186	−0.195
	(0.152)	(0.363)	(0.146)	(0.412)	(0.156)
GFC = 1 ×Subjectivity (S, dict)	0.344	0.020	1.517	2.540	−2.060
	(1.335)	(3.797)	(1.317)	(3.626)	(1.550)
GFC = 1 ×Subjectivity (S, ML)	−3.990**	−6.955*	2.635**	1.638	−0.897
	(1.799)	(3.961)	(1.159)	(3.761)	(1.118)
Observations	1382	1422	1433	1232	1580

GFC = Dummy variable for Global Financial Crisis.
Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

can affect the efficiency and stability of capital markets within and across countries. To our knowledge, only one study (Agarwal et al., 2019) applies textual analysis methods to these reports.

We examine the relationship between the sovereign credit ratings and the reports that accompany them. We achieve this by employing textual (sentiment) analysis methods to S&P, Fitch, and Moody's Rating Action reports, which produces six key indicators: net sentiment, polarity (dictionary-based and machine learning approach), and subjectivity (dictionary-based approach at word and sentence level, and machine learning approach). We partially relate textual sentiment measures to proxies for soft information and to the general country perception and subjectivity measures to the qualitative (expert) knowledge of the rating committee or their interpretation of soft information. We find that soft information plays an important role when assigning sovereign credit ratings since adding the variables for political risk and institutional strength significantly improves the predictability of sovereign credit ratings. We can conclude that improving institutional strength and governance could lead to higher assigned ratings. Furthermore,

Table 10
Estimation results of the random effects model with sentiment and subjectivity measures as dependent variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Institutional quality	−0.076***	−0.012***	−0.009**	0.036**	0.002	−0.003
	(0.026)	(0.003)	(0.004)	(0.017)	(0.002)	(0.002)
Governance	0.187***	0.026***	0.032***	−0.093***	−0.007***	0.003**
	(0.026)	(0.003)	(0.004)	(0.014)	(0.001)	(0.001)
Trade proximity	4.871**	0.635**	1.291***	3.553	0.157	−0.341**
	(2.194)	(0.277)	(0.411)	(2.737)	(0.186)	(0.139)
Common language	−0.156	−0.027	−0.020	−0.083	−0.001	−0.026**
	(0.192)	(0.027)	(0.038)	(0.143)	(0.013)	(0.013)
Religious proximity	0.169	0.022	0.162*	−0.326	−0.015	0.056*
	(0.366)	(0.047)	(0.083)	(0.300)	(0.029)	(0.030)
Geographical distance	0.005*	0.001**	0.001**	0.001	0.000	−0.000
	(0.003)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)
Constant	−5.213***	−0.696***	−0.471***	4.394***	0.456***	0.323***
	(0.605)	(0.077)	(0.108)	(0.377)	(0.037)	(0.035)
Observations	1669	1669	1669	1669	1669	1669
R^2	0.103	0.120	0.153	0.031	0.021	0.034

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict),
(5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

we find evidence of economic proximity bias, which means that credit rating agencies (that are US-based) assign higher credit ratings to countries that have strong trade ties with the US. Results suggest that textual sentiment provides additional information not captured by traditional determinants of sovereign credit ratings, especially if soft information and bias proxies are not taken into account. On the other hand, our analysis indicates that the qualitative judgment of the rating committee manifests itself in the subjectivity score and is robust to model expansions for one of three credit rating agencies. Additionally, we find differences in sentiment between emerging and advanced markets for one of the agencies, which is most likely due to the difference in the general perception of these groups of countries and perceived political risk. We detect a significant difference in subjectivity scores for emerging markets compared to advanced economies, indicating that the rating committee employs different levels of qualitative judgment for these groups of countries. Potential data shortage or low-quality data for emerging markets, and consequently, an increased need for qualitative judgment may explain these differences.

We identify different determinants describing sovereign credit ratings of advanced and emerging countries and some indication of, on the one hand, an upward cultural bias towards the developed world and, on the other hand, an upward economic bias towards the emerging markets. We also detect a change in sentiment after the 2008 global financial crisis, which may be due to the generally negative tone in the economy, but we do not register any difference in subjectivity. Finally, we find that sentiment can partially be explained by soft information and bias proxies, while subjectivity cannot, supporting our initial hypothesis.

The main finding of this paper is thus that the qualitative (expert) judgment of the rating committee can, to some extent, be reflected in the subjectivity indicator obtained from the sovereign credit rating reports. This opens the door to further research opportunities, both in terms of data and methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix

See Tables A.11 and A.21.

Table A.11
List of countries in the sample.

Country	Country	Country	Country	Country
Angola	Czech Republic	Israel	Norway	Switzerland
Argentina	Denmark	Italy	Pakistan	Thailand
Australia	Dominican Republic	Jamaica	Panama	Turkey
Austria	Ecuador	Japan	Papua New Guinea	Uganda
Azerbaijan	Egypt	Kazakhstan	Paraguay	Ukraine
Bangladesh	El Salvador	Kenya	Peru	United Kingdom
Belarus	Estonia	Korea	Philippines	United States
Belgium	Ethiopia	Latvia	Poland	Uruguay
Bolivia	Finland	Lebanon	Portugal	Venezuela
Brazil	France	Lithuania	Romania	Vietnam
Bulgaria	Germany	Luxembourg	Russia	Zambia
Cameroon	Ghana	Malaysia	Saudi Arabia	
Canada	Greece	Malta	Serbia	
Chile	Guatemala	Mexico	Singapore	
China	Hong Kong	Morocco	Slovakia	
Colombia	Hungary	Mozambique	Slovenia	
Congo, Republic of	Iceland	Netherlands	South Africa	
Costa Rica	India	New Zealand	Spain	
Croatia	Indonesia	Nicaragua	Sri Lanka	
Cyprus	Ireland	Nigeria	Sweden	
	S&P	Fitch	Moody's	
	Albania	Armenia	Albania	
	Bahamas, The	Gabon	Armenia	
	Botswana	Gambia, The	Bahamas, The	
	Gabon	Malawi	Botswana	
	Honduras	Moldova	Honduras	
	Jordan	Namibia	Jordan	
		Tunisia	Moldova	
			Namibia	
			Tunisia	

Table A.12
Bivariate analysis of S&P: mean comparison of key variables for advanced economies (AE) and emerging markets (EME), and before and after the Global financial crisis (GFC).

	(1)	(2)	(3)	(4)	(5)	(6)
	A: Emerging markets vs. advanced economies					
Mean (EME)	−1.542	−0.212	0.383	2.671	0.341	0.347
Mean (AE)	−1.009	−0.134	0.474	2.752	0.344	0.343
Diff. in means (EME-AE)	−0.533***	−0.077***	−0.092***	−0.081	−0.003	0.004
	(0.109)	(0.014)	(0.016)	(0.052)	(0.006)	(0.005)
Observations (EME)	831	Observations (Total)			1382	
Observations (AE)	551					
	B: Before vs. after the Global financial crisis (GFC)					
Mean (before GFC)	−1.394	−0.167	0.461	2.290	0.314	0.354
Mean (after GFC)	−1.302	−0.187	0.401	2.881	0.354	0.342
Diff. in means (before-after GFC)	−0.092	0.020	0.060***	−0.591***	−0.040***	0.012**
	(0.125)	(0.015)	(0.017)	(0.054)	(0.006)	(0.006)
Observations (before GFC)	416	Observations (Total)			1382	
Observations (after GFC)	966					
	C: Emerging markets before vs. after the Global financial crisis					
Mean (before GFC)	−1.655	−0.199	0.391	2.319	0.323	0.354
Mean (after GFC)	−1.494	−0.217	0.379	2.820	0.349	0.344
Diff. in means (before-after GFC)	−0.161	0.018	0.012	−0.500***	−0.027***	0.010
	(0.166)	(0.020)	(0.021)	(0.066)	(0.008)	(0.007)
Observations (before GFC)	247	Observations (Total EME)			831	
Observations (after GFC)	584					

(*continued on next page*)

Table A.12 (*continued*).

	(1)	(2)	(3)	(4)	(5)	(6)
	D: Advanced economies before vs. after the Global financial crisis					
Mean (before GFC)	−1.011	−0.120	0.563	2.247	0.302	0.354
Mean (after GFC)	−1.008	−0.141	0.435	2.975	0.362	0.338
Diff. in means (before-after GFC)	−0.003	0.021	0.128***	−0.727***	−0.060***	0.016*
	(0.187)	(0.024)	(0.028)	(0.090)	(0.010)	(0.009)
Observations (before GFC)	169	Observations (Total AE)			551	
Observations (after GFC)	382					
	E: Emerging vs. advanced markets before the Global financial crisis					
Mean (EME)	−1.655	−0.199	0.391	2.319	0.323	0.354
Mean (AE)	−1.011	−0.120	0.563	2.247	0.302	0.354
Diff. in means (EME-AE)	−0.644***	−0.079***	−0.172***	0.072	0.021*	−0.001
	(0.217)	(0.026)	(0.029)	(0.095)	(0.011)	(0.010)
Observations (EME)	247	Observations (Total before GFC)			416	
Observations (AE)	169					
	F: Emerging vs. advanced markets after the Global financial crisis					
Mean (EME)	−1.494	−0.217	0.379	2.820	0.349	0.344
Mean (AE)	−1.008	−0.141	0.435	2.975	0.362	0.338
Diff. in means (EME-AE)	−0.486***	−0.076***	−0.056***	−0.155***	−0.013**	0.006
	(0.124)	(0.017)	(0.019)	(0.058)	(0.006)	(0.006)
Observations (EME)	584	Observations (Total after GFC)			966	
Observations (AE)	382					

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict), (5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13
Bivariate analysis of Fitch: mean comparison of key variables for advanced economies (AE) and emerging markets (EME), and before and after the Global financial crisis (GFC).

	(1)	(2)	(3)	(4)	(5)	(6)
	A: Emerging markets vs. advanced economies					
Mean (EME)	−1.905	−0.218	0.358	3.147	0.375	0.385
Mean (AE)	−1.610	−0.190	0.434	3.118	0.360	0.332
Diff. in means (EME-AE)	−0.295**	−0.028*	−0.076***	0.029	0.015**	0.052***
	(0.125)	(0.015)	(0.016)	(0.063)	(0.006)	(0.007)
Observations (EME)	842	Observations (Total)			1433	
Observations (AE)	591					
	B: Before vs. after the Global financial crisis (GFC)					
Mean (before GFC)	−1.219	−0.137	0.453	2.507	0.323	0.353
Mean (after GFC)	−2.094	−0.244	0.355	3.481	0.394	0.369
Diff. in means (before-after GFC)	0.874***	0.107***	0.099***	−0.974***	−0.071***	−0.016**
	(0.135)	(0.016)	(0.016)	(0.060)	(0.007)	(0.007)
Observations (before GFC)	509	Observations (Total)			1433	
Observations (after GFC)	924					
	C: Emerging markets before vs. after the Global financial crisis					
Mean (before GFC)	−1.294	−0.147	0.403	2.551	0.333	0.387
Mean (after GFC)	−2.244	−0.257	0.334	3.477	0.398	0.383
Diff. in means (before-after GFC)	0.950***	0.110***	0.069***	−0.926***	−0.065***	0.004
	(0.180)	(0.021)	(0.021)	(0.082)	(0.009)	(0.010)
Observations (before GFC)	300	Observations (Total EME)			842	
Observations (after GFC)	542					

(*continued on next page*)

Table A.13 (*continued*).

	(1)	(2)	(3)	(4)	(5)	(6)
	D: Advanced economies before vs. after the Global financial crisis					
Mean (before GFC)	−1.113	−0.123	0.526	2.444	0.308	0.304
Mean (after GFC)	−1.882	−0.226	0.384	3.487	0.388	0.348
Diff. in means (before-after GFC)	0.769***	0.103***	0.142***	−1.043***	−0.080***	−0.044***
	(0.203)	(0.025)	(0.024)	(0.085)	(0.009)	(0.010)
Observations (before GFC)	209	Observations (Total AE)			591	
Observations (after GFC)	382					
	E: Emerging vs. advanced markets before the Global financial crisis					
Mean (EME)	−1.294	−0.147	0.403	2.551	0.333	0.387
Mean (AE)	−1.113	−0.123	0.526	2.444	0.308	0.304
Diff. in means (EME-AE)	−0.181	−0.024	−0.123***	0.107	0.025**	0.083***
	(0.230)	(0.029)	(0.026)	(0.092)	(0.011)	(0.012)
Observations (EME)	300	Observations (Total before GFC)			509	
Observations (AE)	209					
	F: Emerging vs. advanced markets after the Global financial crisis					
Mean (EME)	−2.244	−0.257	0.334	3.477	0.398	0.383
Mean (AE)	−1.882	−0.226	0.384	3.487	0.388	0.348
Diff. in means (EME-AE)	−0.362**	−0.031*	−0.050***	−0.010	0.010	0.035***
	(0.144)	(0.016)	(0.019)	(0.074)	(0.007)	(0.008)
Observations (EME)	542	Observations (Total after GFC)			924	
Observations (AE)	382					

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict),
(5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14
Bivariate analysis of Moody's: mean comparison of key variables for advanced economies (AE) and emerging markets (EME), and before and after the Global financial crisis (GFC).

	(1)	(2)	(3)	(4)	(5)	(6)
	A: Emerging markets vs. advanced economies					
Mean (EME)	−1.379	−0.160	0.239	2.404	0.299	0.430
Mean (AE)	−0.791	−0.101	0.362	2.516	0.309	0.443
Diff. in means (EME-AE)	−0.588***	−0.059***	−0.122***	−0.113*	−0.009	−0.013
	(0.123)	(0.018)	(0.024)	(0.063)	(0.006)	(0.008)
Observations (EME)	982	Observations (Total)			1580	
Observations (AE)	598					
	B: Before vs. after the Global financial crisis (GFC)					
Mean (before GFC)	−0.907	−0.104	0.377	2.015	0.270	0.499
Mean (after GFC)	−1.313	−0.159	0.229	2.718	0.324	0.395
Diff. in means (before-after GFC)	0.407***	0.055***	0.148***	−0.703***	−0.054***	0.104***
	(0.134)	(0.018)	(0.024)	(0.059)	(0.007)	(0.008)
Observations (before GFC)	769	Observations (Total)			1580	
Observations (after GFC)	811					
	C: Emerging markets before vs. after the Global financial crisis					
Mean (before GFC)	−1.220	−0.139	0.288	2.066	0.271	0.496
Mean (after GFC)	−1.485	−0.174	0.207	2.630	0.318	0.386
Diff. in means (before-after GFC)	0.265	0.036	0.081***	−0.565***	−0.047***	0.110***
	(0.183)	(0.024)	(0.030)	(0.072)	(0.008)	(0.010)
Observations (before GFC)	485	Observations (Total EME)			982	
Observations (after GFC)	497					

(*continued on next page*)

Table A.14 (*continued*).

	(1)	(2)	(3)	(4)	(5)	(6)
	D: Advanced economies before vs. after the Global financial crisis					
Mean (before GFC)	−0.335	−0.040	0.538	1.921	0.267	0.503
Mean (after GFC)	−1.048	−0.135	0.262	2.853	0.332	0.409
Diff. in means (before-after GFC)	0.714***	0.095***	0.277***	−0.932***	−0.065***	0.094***
	(0.174)	(0.028)	(0.036)	(0.099)	(0.011)	(0.013)
Observations (before GFC)	284	Observations (Total AE)			598	
Observations (after GFC)	314					
	E: Emerging vs. advanced markets before the Global financial crisis					
Mean (EME)	−1.220	−0.139	0.288	2.066	0.271	0.496
Mean (AE)	−0.335	−0.040	0.538	1.921	0.267	0.503
Diff. in means (EME-AE)	−0.885***	−0.098***	−0.250***	0.145	0.004	−0.007
	(0.203)	(0.030)	(0.036)	(0.099)	(0.012)	(0.014)
Observations (EME)	485	Observations (Total before GFC)			769	
Observations (AE)	284					
	F: Emerging vs. advanced markets after the Global financial crisis					
Mean (EME)	−1.485	−0.174	0.207	2.630	0.318	0.386
Mean (AE)	−1.048	−0.135	0.262	2.853	0.332	0.409
Diff. in means (EME-AE)	−0.437***	−0.039*	−0.055*	−0.223***	−0.014**	−0.023***
	(0.151)	(0.022)	(0.030)	(0.073)	(0.007)	(0.009)
Observations (EME)	497	Observations (Total after GFC)			811	
Observations (AE)	314					

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict),
(5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15
S&P: Estimation results of Model 3 with sentiment and subjectivity scores of the ordered logit with random effect for the determinants of sovereign credit ratings.

	Sovereign credit ratings					
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita	0.181***	0.181***	0.188***	0.183***	0.183***	0.183***
	(0.054)	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)
Real GDP growth	0.129	−0.129	−0.510	0.490	0.476	0.613
	(3.725)	(3.686)	(3.541)	(3.739)	(3.742)	(3.782)
Inflation	−7.031***	−6.988***	−6.585***	−7.124***	−7.070***	−7.307***
	(2.075)	(2.074)	(2.034)	(2.113)	(2.123)	(2.080)
Current account/GDP	−5.046**	−5.211**	−5.167**	−4.879**	−4.880**	−4.902**
	(2.059)	(2.046)	(2.032)	(2.063)	(2.066)	(2.055)
Trade/GDP	1.202*	1.179	1.239*	1.231*	1.236*	1.218*
	(0.729)	(0.726)	(0.753)	(0.733)	(0.734)	(0.728)
External debt/GDP	−0.004	−0.000	0.006	−0.008	−0.006	−0.014
	(0.148)	(0.148)	(0.152)	(0.148)	(0.149)	(0.147)
Economic development	5.706***	5.737***	5.662***	5.677***	5.674***	5.693***
	(1.941)	(1.936)	(1.969)	(1.944)	(1.945)	(1.939)
Default history	−3.146***	−3.182***	−3.325***	−3.107***	−3.111***	−3.103***
	(0.952)	(0.950)	(0.950)	(0.952)	(0.947)	(0.953)
Log of int. reserves	0.600*	0.597*	0.569	0.620*	0.620*	0.617*
	(0.359)	(0.357)	(0.361)	(0.360)	(0.358)	(0.353)
Government debt/GDP	−8.147***	−8.131***	−8.335***	−8.150***	−8.174***	−8.062***
	(1.274)	(1.275)	(1.274)	(1.259)	(1.268)	(1.276)
Budget balance/GDP	−4.717	−4.989	−5.331	−4.461	−4.515	−4.222
	(3.391)	(3.375)	(3.415)	(3.336)	(3.360)	(3.328)
Institutional quality	0.110	0.108	0.107	0.110	0.110	0.104
	(0.160)	(0.160)	(0.161)	(0.160)	(0.160)	(0.160)

(*continued on next page*)

Table A.15 (*continued*).

	Sovereign credit ratings					
	(1)	(2)	(3)	(4)	(5)	(6)
Governance	0.467***	0.464***	0.454***	0.466***	0.466***	0.465***
	(0.061)	(0.061)	(0.059)	(0.059)	(0.060)	(0.060)
Trade proximity	69.019***	68.700***	69.597***	68.613***	68.552***	68.677***
	(22.072)	(21.986)	(21.937)	(22.237)	(22.143)	(22.099)
Common language	−0.659	−0.654	−0.706	−0.654	−0.654	−0.628
	(0.815)	(0.814)	(0.841)	(0.813)	(0.815)	(0.809)
Religious proximity	1.462	1.466	1.275	1.445	1.435	1.483
	(1.725)	(1.729)	(1.777)	(1.702)	(1.706)	(1.701)
Geographical distance	0.011	0.011	0.010	0.011	0.011	0.011
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
Net sentiment (W, dict)	0.033					
	(0.048)					
Polarity (W, dict)		0.458				
		(0.347)				
Polarity (S, ML)			1.024***			
			(0.324)			
Subjectivity (W, dict)				−0.023		
				(0.087)		
Subjectivity (S, dict)					−0.365	
					(0.733)	
Subjectivity (S, ML)						0.766
						(0.720)
Observations	1382	1382	1382	1382	1382	1382

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict),
(5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Clustered standard errors in parentheses.
Cut-off estimates are not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.16
Fitch: Estimation results of Model 3 with sentiment and subjectivity scores of the ordered logit with random effect for the determinants of sovereign credit ratings.

	Sovereign credit ratings					
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita	0.196***	0.196***	0.199***	0.194***	0.197***	0.196***
	(0.055)	(0.055)	(0.056)	(0.055)	(0.056)	(0.055)
Real GDP growth	−3.012	−2.789	−3.841	−2.599	−2.794	−2.691
	(3.132)	(3.203)	(3.048)	(3.159)	(3.246)	(3.220)
Inflation	−5.740**	−5.795**	−5.386**	−5.699**	−5.868**	−5.790**
	(2.398)	(2.397)	(2.328)	(2.347)	(2.371)	(2.376)
Current account/GDP	−3.850***	−3.791***	−4.026***	−3.784***	−3.806***	−3.797***
	(1.395)	(1.392)	(1.438)	(1.415)	(1.414)	(1.412)
Trade/GDP	0.980	0.986	1.081	0.943	1.018	0.999
	(0.682)	(0.680)	(0.690)	(0.678)	(0.677)	(0.681)
External debt/GDP	−0.183**	−0.184**	−0.180**	−0.180**	−0.186**	−0.185**
	(0.074)	(0.073)	(0.076)	(0.072)	(0.073)	(0.073)
Economic development	7.114***	7.100***	7.141***	7.142***	7.074***	7.101***
	(1.787)	(1.788)	(1.801)	(1.805)	(1.795)	(1.789)
Default history	−5.234***	−5.226***	−5.195***	−5.226***	−5.237***	−5.237***
	(0.996)	(1.007)	(0.971)	(1.008)	(1.008)	(1.010)
Log of int. reserves	0.553**	0.555**	0.550**	0.531**	0.570**	0.553**
	(0.258)	(0.256)	(0.266)	(0.263)	(0.262)	(0.256)
Government debt/GDP	−8.426***	−8.408***	−8.453***	−8.463***	−8.371***	−8.408***
	(1.072)	(1.077)	(1.065)	(1.083)	(1.081)	(1.078)

(*continued on next page*)

Table A.16 (*continued*).

	Sovereign credit ratings					
	(1)	(2)	(3)	(4)	(5)	(6)
Budget balance/GDP	−5.708*	−5.434	−7.334**	−5.233	−5.449*	−5.414
	(3.392)	(3.401)	(3.358)	(3.277)	(3.283)	(3.293)
Institutional quality	−0.022	−0.023	−0.017	−0.020	−0.027	−0.025
	(0.132)	(0.132)	(0.133)	(0.131)	(0.130)	(0.130)
Governance	0.448***	0.451***	0.436***	0.459***	0.448***	0.451***
	(0.060)	(0.060)	(0.058)	(0.059)	(0.058)	(0.060)
Trade proximity	31.668***	31.824***	32.179***	32.312***	31.433***	31.795***
	(10.155)	(10.151)	(10.708)	(10.139)	(10.148)	(10.179)
Common language	−1.149	−1.150	−1.189	−1.152	−1.148	−1.154
	(0.848)	(0.845)	(0.855)	(0.849)	(0.844)	(0.846)
Religious proximity	−0.924	−0.899	−0.982	−0.911	−0.891	−0.903
	(1.576)	(1.570)	(1.597)	(1.580)	(1.574)	(1.573)
Geographical distance	−0.009	−0.009	−0.009	−0.009	−0.009	−0.009
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Net sentiment (W, dict)	0.021					
	(0.043)					
Polarity (W, dict)		0.042				
		(0.370)				
Polarity (S, ML)			1.010***			
			(0.310)			
Subjectivity (W, dict)				0.058		
				(0.086)		
Subjectivity (S, dict)					−0.473	
					(0.686)	
Subjectivity (S, ML)						−0.228
						(0.602)
Observations	1433	1433	1433	1433	1433	1433

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict),
(5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Clustered standard errors in parentheses.
Cut-off estimates are not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17
Moody's: Estimation results of Model 3 with sentiment and subjectivity scores of the ordered logit with random effect for the determinants of sovereign credit ratings.

	Sovereign credit ratings					
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita	0.162***	0.162***	0.164***	0.172***	0.167***	0.159***
	(0.051)	(0.051)	(0.052)	(0.053)	(0.052)	(0.051)
Real GDP growth	−2.323	−2.147	−2.486	−1.900	−1.960	−1.986
	(2.132)	(2.133)	(2.224)	(2.268)	(2.231)	(2.226)
Inflation	−2.781	−2.838	−2.728	−2.781	−2.840	−2.936
	(2.442)	(2.459)	(2.406)	(2.451)	(2.434)	(2.441)
Current account/GDP	−4.783**	−4.779**	−4.720**	−4.703**	−4.745**	−4.740**
	(2.061)	(2.050)	(2.037)	(2.012)	(2.040)	(2.067)
Trade/GDP	−0.133	−0.138	−0.122	−0.069	−0.112	−0.165
	(0.607)	(0.609)	(0.608)	(0.605)	(0.605)	(0.626)
External debt/GDP	−0.130*	−0.130*	−0.133*	−0.139*	−0.134*	−0.127*
	(0.075)	(0.075)	(0.075)	(0.075)	(0.076)	(0.075)
Economic development	5.507***	5.498***	5.481***	5.448***	5.501***	5.662***
	(1.699)	(1.692)	(1.694)	(1.647)	(1.653)	(1.718)
Default history	−5.601***	−5.564***	−5.575***	−5.572***	−5.583***	−5.603***
	(1.211)	(1.215)	(1.213)	(1.207)	(1.215)	(1.242)

(*continued on next page*)

Table A.17 (*continued*).

	Sovereign credit ratings					
	(1)	(2)	(3)	(4)	(5)	(6)
Log of int. reserves	0.455**	0.456**	0.465**	0.509***	0.484**	0.430**
	(0.194)	(0.195)	(0.194)	(0.190)	(0.190)	(0.191)
Government debt/GDP	−7.309***	−7.325***	−7.325***	−7.382***	−7.372***	−7.448***
	(1.163)	(1.163)	(1.151)	(1.142)	(1.149)	(1.173)
Budget balance/GDP	−5.805*	−5.739*	−5.999*	−5.674*	−5.747*	−5.585*
	(3.456)	(3.482)	(3.470)	(3.401)	(3.487)	(3.385)
Institutional quality	−0.009	−0.010	−0.016	−0.027	−0.022	−0.017
	(0.103)	(0.103)	(0.103)	(0.099)	(0.100)	(0.102)
Governance	0.415***	0.419***	0.416***	0.410***	0.417***	0.432***
	(0.053)	(0.053)	(0.052)	(0.051)	(0.051)	(0.050)
Trade proximity	31.516***	31.654***	31.070***	32.194***	31.521***	32.408***
	(8.810)	(8.870)	(8.831)	(9.180)	(8.875)	(8.934)
Common language	−0.342	−0.345	−0.337	−0.328	−0.328	−0.387
	(0.690)	(0.690)	(0.690)	(0.693)	(0.691)	(0.700)
Religious proximity	0.755	0.745	0.687	0.790	0.739	0.749
	(1.393)	(1.394)	(1.392)	(1.374)	(1.373)	(1.411)
Geographical distance	0.011	0.011	0.011	0.012	0.012	0.012
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Net sentiment (W, dict)	0.043					
	(0.037)					
Polarity (W, dict)		0.214				
		(0.285)				
Polarity (S, ML)			0.325			
			(0.207)			
Subjectivity (W, dict)				−0.198**		
				(0.091)		
Subjectivity (S, dict)					−1.301*	
					(0.774)	
Subjectivity (S, ML)						−0.810
						(0.673)
Observations	1580	1580	1580	1580	1580	1580

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict),
(5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Clustered standard errors in parentheses.
Cut-off estimates are not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18
Estimation results of sentiment and subjectivity scores from the fixed effects, random effects, pooled OLS and ordered logit for the determinants of sovereign credit ratings.

	Sovereign credit ratings			
	Fixed Effects	Random Effects	Pooled OLS	Ordered logit
	S&P			
Net sentiment (W, dict)	0.000	0.009	0.035	0.041
	(0.024)	(0.026)	(0.032)	(0.038)
Polarity (W, dict)	0.173	0.234	0.397	0.439
	(0.176)	(0.188)	(0.251)	(0.300)
Polarity (S, ML)	0.460**	0.464**	0.526**	0.846**
	(0.181)	(0.195)	(0.251)	(0.330)
Subjectivity (W, dict)	0.010	0.001	−0.023	−0.016
	(0.048)	(0.051)	(0.089)	(0.086)
Subjectivity (S, dict)	0.291	0.195	0.211	0.008
	(0.356)	(0.382)	(0.665)	(0.619)
Subjectivity (S, ML)	1.273***	1.092***	1.473*	1.257
	(0.402)	(0.421)	(0.853)	(0.850)

(*continued on next page*)

Table A.18 (*continued*).

	Sovereign credit ratings			
	Fixed Effects	Random Effects	Pooled OLS	Ordered logit
	Fitch			
Net sentiment (W, dict)	0.025	0.018	0.033	0.009
	(0.022)	(0.023)	(0.030)	(0.035)
Polarity (W, dict)	0.079	0.048	0.367	0.167
	(0.177)	(0.187)	(0.275)	(0.314)
Polarity (S, ML)	0.538***	0.531***	0.712**	0.695**
	(0.178)	(0.182)	(0.308)	(0.311)
Subjectivity (W, dict)	−0.008	0.007	0.082	0.046
	(0.044)	(0.045)	(0.060)	(0.075)
Subjectivity (S, dict)	−0.380	−0.231	0.316	−0.140
	(0.335)	(0.334)	(0.494)	(0.672)
Subjectivity (S, ML)	−0.097	0.056	0.157	−0.224
	(0.292)	(0.298)	(0.462)	(0.625)
	Moody's			
Net sentiment (W, dict)	0.042*	0.035	−0.011	0.007
	(0.024)	(0.023)	(0.027)	(0.033)
Polarity (W, dict)	0.341*	0.285	−0.094	−0.058
	(0.182)	(0.174)	(0.211)	(0.261)
Polarity (S, ML)	0.193*	0.164	−0.121	0.011
	(0.112)	(0.115)	(0.173)	(0.227)
Subjectivity (W, dict)	−0.076	−0.077	−0.051	−0.148*
	(0.056)	(0.058)	(0.088)	(0.088)
Subjectivity (S, dict)	−0.684	−0.635	−0.183	−0.507
	(0.522)	(0.512)	(0.742)	(0.762)
Subjectivity (S, ML)	−0.677	−0.576	−0.176	0.049
	(0.419)	(0.416)	(0.550)	(0.552)
Observations	S&P	1382		
	Fitch	1433		
	Moody's	1580		

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.19
Estimation results of Model 3 of the ordered logit with random effects for the determinants of sovereign credit ratings of advanced economies and emerging markets.

	Sovereign credit ratings					
	S&P		Fitch		Moody's	
	AE	EME	AE	EME	AE	EME
GDP per capita	0.090	0.274***	0.149**	0.331***	0.100	0.320***
	(0.068)	(0.091)	(0.074)	(0.081)	(0.069)	(0.085)
Real GDP growth	−10.532	6.814*	−9.900	1.615	−14.622***	0.510
	(7.080)	(3.887)	(9.038)	(3.055)	(5.050)	(2.341)
Inflation	−25.371***	−5.220***	−26.991***	−3.751*	−34.520***	−2.016
	(5.073)	(1.848)	(10.475)	(2.045)	(7.422)	(2.153)
Current account/GDP	−8.207**	−5.026*	−8.677***	−4.855***	−17.557***	−2.358
	(3.772)	(2.579)	(3.084)	(1.694)	(3.610)	(2.506)
Trade/GDP	7.634***	−0.230	4.967***	−0.446	5.943***	−0.518
	(1.985)	(1.121)	(1.830)	(0.980)	(1.417)	(1.002)
External debt/GDP	−0.112	0.666	−0.303**	0.328	−0.146	0.051
	(0.184)	(1.432)	(0.138)	(1.047)	(0.208)	(1.092)
Default history	0.008	−3.438***	−0.597	−5.388***	−1.246	−5.429***
	(1.373)	(1.042)	(1.699)	(1.081)	(1.977)	(1.085)

(*continued on next page*)

Table A.19 (*continued*).

	Sovereign credit ratings					
	S&P		Fitch		Moody's	
	AE	EME	AE	EME	AE	EME
Log of int. reserves	−1.124***	1.482***	−1.026***	1.272***	−0.813**	0.714***
	(0.411)	(0.295)	(0.361)	(0.284)	(0.335)	(0.243)
Government debt/GDP	−15.542***	−7.280***	−12.844***	−7.081***	−15.584***	−5.450***
	(3.293)	(1.214)	(2.332)	(1.193)	(2.969)	(1.172)
Budget balance/GDP	−1.756	−1.816	−4.100	−1.779	−3.138	−5.916
	(5.465)	(4.088)	(11.023)	(3.724)	(6.705)	(4.331)
Institutional quality	0.953*	−0.041	−0.157	−0.035	−0.771**	0.066
	(0.500)	(0.194)	(0.329)	(0.177)	(0.388)	(0.122)
Governance	0.489***	0.496***	0.476***	0.448***	0.672***	0.346***
	(0.086)	(0.075)	(0.103)	(0.078)	(0.088)	(0.056)
Trade proximity	−117.444	67.723***	−79.349*	61.900**	−70.847	36.929**
	(127.048)	(24.970)	(46.060)	(30.532)	(53.024)	(16.482)
Common language	6.737	0.302	1.259	−0.973	5.472	−0.150
	(8.464)	(1.132)	(2.049)	(0.982)	(5.318)	(0.925)
Religious proximity	18.466***	0.998	6.855	−1.715	15.794**	−0.165
	(6.681)	(1.819)	(6.806)	(1.551)	(6.399)	(1.334)
Geographical distance	−0.026	0.013	−0.090**	0.005	−0.018	0.015
	(0.087)	(0.013)	(0.040)	(0.012)	(0.020)	(0.010)
Observations	551	831	591	842	598	982

AE = Advanced economies, EME = Emerging markets.
Clustered standard errors in parentheses.
Cut-off estimates are not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.20
Estimation results of Model 3 with sentiment and subjectivity measures of the ordered logit with random effects for the determinants of sovereign credit ratings of advanced economies and emerging markets.

	Sovereign credit ratings					
	S&P		Fitch		Moody's	
	AE	EME	AE	EME	AE	EME
Net sentiment (W, dict)	0.099	−0.029	0.008	0.040	0.034	0.058
	(0.338)	(0.050)	(0.067)	(0.057)	(0.091)	(0.049)
Polarity (W, dict)	0.767	0.112	0.086	0.172	0.328	0.243
	(0.648)	(0.392)	(0.642)	(0.504)	(0.588)	(0.371)
Polarity (S, ML)	0.428	1.099***	0.612	1.176***	0.346	0.273
	(0.547)	(0.375)	(0.461)	(0.429)	(0.404)	(0.269)
Subjectivity (W, dict)	0.053	0.016	0.007	−0.072	0.029	−0.190*
	(0.158)	(0.122)	(0.142)	(0.100)	(0.181)	(0.109)
Subjectivity (S, dict)	0.317	−0.017	−2.109	−1.076	−0.110	−1.378
	(1.041)	(0.961)	(1.325)	(0.902)	(1.629)	(0.985)
Subjectivity (S, ML)	0.940	1.987**	0.401	−0.237	0.165	−0.780
	(1.514)	(0.883)	(1.340)	(0.795)	(1.098)	(0.847)
Observations	551	831	591	842	598	982

AE = Advanced economies, EME = Emerging markets.
Clustered standard errors in parentheses.
Cut-off estimates are not reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.21
Estimation results of the random effects model with sentiment and subjectivity measures as dependent variables for subcomponents of governance and institutional quality.

	(1)	(2)	(3)	(4)	(5)	(6)
Trade proximity	5.943***	0.813***	1.638***	0.327	−0.126	−0.217**
	(2.208)	(0.278)	(0.432)	(1.854)	(0.146)	(0.105)
Common language	−0.138	−0.027	−0.022	−0.005	0.008	−0.030**
	(0.206)	(0.028)	(0.039)	(0.117)	(0.011)	(0.013)
Religious proximity	−0.147	−0.027	0.105	−0.130	−0.000	0.040
	(0.403)	(0.050)	(0.088)	(0.253)	(0.026)	(0.030)
Geographical distance	0.006**	0.001**	0.001***	0.002	0.000	−0.000
	(0.003)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)
Government stability	0.121**	0.020***	0.033***	−0.199***	−0.015***	0.012***
	(0.058)	(0.007)	(0.009)	(0.023)	(0.003)	(0.002)
Socioeconomic conditions	0.187***	0.024***	0.020*	0.113***	0.012***	−0.005
	(0.066)	(0.007)	(0.010)	(0.033)	(0.004)	(0.004)
Investment profile	0.272***	0.038***	0.044***	−0.132***	−0.012***	0.002
	(0.057)	(0.007)	(0.009)	(0.028)	(0.003)	(0.003)
Corruption	0.201	0.015	0.009	−0.054	−0.009	−0.011
	(0.129)	(0.017)	(0.021)	(0.052)	(0.005)	(0.007)
Law and order	−0.211**	−0.028**	−0.014	−0.121**	−0.012**	0.001
	(0.105)	(0.013)	(0.016)	(0.051)	(0.005)	(0.006)
Democratic accountability	−0.022	0.001	0.009	−0.013	0.001	0.008
	(0.075)	(0.009)	(0.017)	(0.053)	(0.005)	(0.006)
Bureaucracy quality	−0.474**	−0.058***	−0.054	0.148	0.013	0.005
	(0.188)	(0.021)	(0.033)	(0.115)	(0.011)	(0.010)
Constant	−4.879***	−0.679***	−0.493***	5.020***	0.510***	0.271***
	(0.721)	(0.088)	(0.128)	(0.343)	(0.034)	(0.039)
Observations	1669	1669	1669	1669	1669	1669
R^2						

(1) Net sentiment (W, dict), (2) Polarity (W, dict), (3) Polarity (S, ML), (4) Subjectivity (W, dict), (5) Subjectivity (S, dict), (6) Subjectivity (S, ML).
Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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