Can Trust Enhance Credit Rating Accuracy?

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Abstract

This study investigates the role of trust in credit rating accuracy. Utilizing data from 10,832 issuances by 916 firms in the U.S. primary bond market from 2000 to 2023, we show robust evidence that a higher trust between the rating analysts (RA) and the CEO is associated with a more accurate rating. This finding highlights trust's role in facilitating effective information exchange and reducing verification costs, with mutual trust proving especially critical. Furthermore, we find that rating analysts' trust in the CEO enhances rating accuracy when managerial information quality is high and analysts are experienced. Additionally, RA trust drives greater effort, further enhancing accuracy. Trust becomes particularly valuable when physical distance hinders direct communication or external information is scarce. Finally, we find that trust significantly reduces the number of covenants in bond agreements, suggesting trust acts as a substitute for formal contracting mechanisms, reducing the need for restrictive covenants.

Keywords: Trust; Rating Analysts; Rating Accuracy; Corporate Bond

1. Introduction

In the modern financial market, trust acts as an intangible bond, not only promoting transaction efficiency (Coleman, 1988) but also reducing information asymmetry, fostering trade and investment between countries, and stimulating stock market participation (Guiso, Sapienza, & Zingales, 2008; 2009). Trust is widely recognized as a lubricant for financial relationships, facilitating the efficient allocation of resources (Duarte, Siegel, & Young, 2012). However, trust is not without risks. Excessive trust can lead to the spread of misleading information or overreliance on low-quality data in certain contexts (Healy & Palepu, 2001). For example, Bae, Kwon, & Lim (2023) document that over-trust between the board of directors and the CEO negatively affects the M&A performance, illuminating the potentially negative effects of trust in corporate governance. The role of trust has been learned in multiple contexts, including the stock market (Pursiainen, 2022), bank loans (Hagendorff, Lee, & Li, 2023), venture capital (Bottazzi, Da Rin, & Hellmann, 2016), and financial analysts (Bhagwat & Liu, 2020).[1] We know little about how trust plays a role in the bond market, especially whether and how it affects credit rating accuracy. Along this line, this study aims to explore whether and how the trust of rating analyst (RA) in the CEO enhances or worsens rating accuracy?

We establish our hypotheses based on the information flow from the CEOs to the rating analysts, emphasizing the dynamic relationship between them. Signaling theory suggests that CEOs are incentivized to release information to investors and rating analysts to convey the firm's quality, secure better ratings, and reduce financing costs (Spence, 1973). However, the effectiveness of this information exchange depends on the RA's ability to interpret and verify the information provided. Certain informal characteristics among analysts, such as gender or cultural similarities, may help to verify ambiguous information (Guiso et al., 2009). Yet, some signals remain noisy and difficult to validate, leading to potential inaccuracies in ratings. In this context, trust plays a crucial role in facilitating the effective exchange of information, reducing verification costs, and fostering collaboration, ultimately improving rating accuracy.

Specifically, we propose three hypotheses: (1) higher trust from CEO toward RA enables the sharing of sensitive and detailed information, contributing to more accurate credit ratings; (2) higher trust from RA towards CEO improves analysts' ability to interpret and incorporate managerial insights, particularly in complex or ambiguous contexts, as trusted

[1] Trust has been widely researched across various financial markets, highlighting its varied impacts. In the stock market, trust significantly influences analysts' forecasts; for example, Pursiainen (2022) found that higher trust leads to more optimistic earnings forecasts. In the bank loan market, trust has been shown to affect loan conditions, with Hagendorff, Lee, & Li (2023) demonstrating that lenders' trust in CEOs results in lower interest rates for syndicated loans. In the venture capital market, trust plays a dual role; Bottazzi, Da Rin, & Hellmann (2016) observed that while trust positively correlates with investment decisions, it is negatively associated with successful exits, indicating that trust can both facilitate initial investments and complicate their outcomes. Additionally, in the realm of financial analysts, Bhagwat & Liu (2020) explored how trust influences information processing, emphasizing that trust enhances the accuracy and reliability of analysts' assessments by improving the quality of information exchanged.

information reduces information asymmetry (Coleman, 1988); and (3) mutual trust between CEO and RA fosters open communication, reduces bias, and strengthens long-term collaboration, creating a foundation for highly accurate credit assessments.

To empirically test these hypotheses, we design a series of tests to investigate the impact of trust from RAs to CEOs on the accuracy of Moody's credit ratings. The sample covers bond-issue observations from 2000 Q1 to 2023 Q2, involving 10,832 issuances across 916 U.S. firms. We calculate the rating inaccuracy based on subsequent rating revisions within one year of the initial rating. Trust levels are measured using Eurobarometer survey data and linked to the surnames of RAs and CEOs via *Ancestry.com* to derive trust scores（Bae et al., 2023; Hagendorff et al., 2023; Bhagwat & Liu, 2020). Specifically, we use responses from Eurobarometer surveys to construct a trust matrix reflecting the trust levels from respondents in 16 European countries towards 27 countries. This matrix quantifies the trust level between RA and CEO based on the probability distributions of their surnames' origins. We also factor in the probability of these origins to account for respondents with multiple country origins rather than a single origin.

Our methodology employs ordinary least squares (OLS) regression models with fixed effects to control for firm, year, and analyst-specific factors. These models incorporate bond-level, firm-level, and pair-level control variables to isolate the effect of trust on credit rating accuracy. The empirical results consistently show a significant negative association between trust—whether from the CEO to the RA, the RA to the CEO, or mutual trust—and credit rating inaccuracy. This results emphasizing that higher levels of trust generally lead to more accurate credit ratings. Our findings support the hypothesis that when RAs have a high level of trust in the CEO, they are more likely to accept potentially valuable insights within noisy information, interpreting it with a more open and inclusive attitude. Trust reduces validation costs by enabling RAs to identify and leverage key signals that might otherwise be overlooked due to verification difficulties, ultimately enhancing credit rating accuracy. The results are both statistically and economically significant. Specifically, a one-standard-deviation increase in trust reduces average rating inaccuracy by 0.087 standard deviations.[2]

In addition, we document that RA's trust in the CEO improves rating accuracy under specific conditions. Our Mechanism analysis shows that trust enhances rating accuracy when

[2] This result is calculated by dividing the coefficient of -0.014 (from model [3] in Table 2, which is the baseline results) by the standard deviation of inaccuracy (0.16), resulting in a value of -0.0875.

managerial information quality is high, measured by lower discretionary accruals and fewer fraud restatements. Experienced analysts, indicated by seniority, experience, and tenure, benefit more from trust, leveraging their expertise to extract useful information from noisy signals. Analysts who trust the CEO invest greater effort in preparing reports for the issuer. This increased effort fosters deeper analysis and more comprehensive evaluations, allowing analysts to assess the firm from various angles and improve the accuracy of their ratings. Trust plays a crucial role when direct communication is hindered by physical distance or when external information is scarce, helping to bridge the informational gaps created by asymmetry. We also explore the effect of trust on bond spreads and covenants, revealing that while trust does not significantly impact bond spreads, it significantly reduces the number of covenants in bond agreements. This suggests that trust acts as a substitute for formal contracting mechanisms, reducing the need for restrictive covenants when trust levels are high.

To mitigate endogeneity concerns in our results, we conducted a series of additional tests. First, we included supplementary control variables to mitigate omitted variable bias. These controls incorporate six cultural distance measures (Hofstede, 1984, 2010), additional rating analyst characteristics, as well as CEO specific fixed effects, ensuring that unobserved heterogeneity does not drive the results. The findings remain significant even after accounting for these variables, demonstrating the robustness of the trust-rating accuracy relationship. Second, we tested for reverse causality by examining whether changes in CEO leadership influence RA turnover at Moody's. Using CEO exogenous events, such as unexpected deaths, we find no significant relationship between CEO changes and RA turnover. This rules out the possibility of reverse causality, confirming that trust from the RA to the CEO is not influenced by changes in the CEO position.

To further validate the robustness of our findings, we employed several alternative measures of rating inaccuracy, including shorter-term rating changes (e.g., within nine months) and binary indicators of whether ratings change within one year. These alternative measures yield consistent results, confirming the stability and reliability of our findings and demonstrating that the trust-rating accuracy relationship holds across different contexts and model specifications. We also incorporated secondary RA and CFO to evaluate the influence of additional relationships within the rating process[3]. Results show that trust between the lead RA and the CEO uniquely affects rating accuracy, while trust involving secondary RA or CFO does not. This does not imply that CFO are unimportant or fail to provide valuable information. Rather, it highlights that trust plays a more critical role in processing soft information, such as insights into a company's strategy, leadership, and market potential—areas where the CEO's influence is most significant. In contrast, financial information provided by CFOs is typically audited and categorized as hard data, with clear metrics and verification mechanisms, making trust less essential in its interpretation.

This research contributes to the existing literature in several ways. First, our study contributes to the trust literature by focusing on its role in producing credit ratings. Previous research has focused on studying the effect of trust on equity analysts. For example, Pursiainen (2022) demonstrates that higher cultural trust from equity analysts toward firms leads to positively biased forecasts, showing that trust can sometimes distort objective analysis. Bhagwat and Liu (2020) examine how equity analysts' overall trust in the outside world affects forecast accuracy and find that higher trust improves forecast precision, suggesting that trust can enhance the quality of information processing. Therefore, we complement the previous literature by learning the role of trust for credit rating analysts. In addition, the social trust in Bhagwat and Liu (2020) is a person-level trait that captures the overall value of analysts, while we focus on how trust from RAs to specific CEOs affects information production. Our approach could identify the direction of trust, thus more accurately evaluating how RAs evaluate the noisy information received from the CEO.

Second, our study enhances the understanding of how human factors influence information production in the financial market. Previous studies, such as those by Kempf (2020) and Cornaggia, Cornaggia & Xia (2017), have established that analysts' incentives and career paths influence their rating behavior and outcomes. Fracassi, Petry & Tate (2016) demonstrate that the subjectivity of rating analysts can significantly affect corporate bond prices. Moreover, Wang and Weitzner (2023) show how subjective beliefs of rating agencies influence credit markets, while Hagendorff et al. (2023) demonstrate the impact of trust on bank loan contracts, highlighting the broader implications of human factors in financial decision-making. Our study extends this understanding by demonstrating that interpersonal

[3] We consider the roles of secondary RA and CFO as they are typically the second most influential individuals in their respective parties. Moody's rating reports often have two signatories, with the first signatory (usually the senior one) considered the primary RA in our research.

trust significantly impacts the quality of information production. We provide empirical evidence on how trust between rating analysts and CEOs influences the accuracy of credit ratings. This finding underscores the importance of considering human factors in the analysis of financial information production. It highlights the potential for trust to mitigate or exacerbate these distortions depending on the context.

Third, this research sheds light on how heterogeneous beliefs are generated and propagated. The literature has documented that rating analysts' forecasts can diverge significantly due to differences in their backgrounds, experiences, and subjective beliefs (Kempf, 2020; Pursiainen, 2022; Wang & Weitzner, 2023). By linking trust levels to cultural backgrounds, our study provides a nuanced understanding of how these heterogeneous beliefs are formed. The results indicate that trust between RAs and CEOs affects how information is gathered, processed, and reported, contributing to the diversity of opinions and assessments in the financial market. This contribution is crucial for developing more accurate financial behavior models that account for market participants' diverse perspectives.

Lastly, this study emphasizes the importance of informal mechanisms like trust in enhancing financial market efficiency. Traditional economic theories often focus on formal mechanisms like regulations and contracts to mitigate information asymmetry and improve market efficiency (Jensen & Meckling, 1976; Spence, 1973). While formal mechanisms like regulatory frameworks and transparency requirements are essential for market functioning, informal mechanisms can also play a vital role. Guiso et al. (2008) found that higher levels of trust promote greater stock market participation, while lower trust levels reduce participation. Guiso et al. (2009) further illustrate how cultural biases influence economic exchange and trust in financial markets. Additionally, Bottazzi et al. (2016) provide evidence that trust is crucial for investment decisions in venture capital, where higher trust levels between investors and entrepreneurs are related to better investment outcomes. Our findings build on this work by showing that trust facilitates RAs to exact useful content from noisy information released by the CEO, leading to more accurate credit ratings and, consequently, more efficient financial markets. This research underscores the need to consider informal mechanisms alongside formal ones in policies aimed at improving market outcomes.

The remainder of the research paper is organized as follows: Section 2 reviews the previous literature on credit rating and trust and describes empirical hypothesis development. Section 3 introduces the research data and methodology. Section 4 presents the empirical results. Section 5 provides conclusions.

2. Literature Review and Hypothesis Development

2.1 Roles and Influences Factors of Credit Rating

Credit rating agencies (CRAs) play a critical role in financial markets by evaluating issuers' creditworthiness. These evaluations significantly influence investor decisions, market perceptions, and the cost of capital for issuers. Boot, Milbourn & Schmeits (2006) highlight that credit ratings function as coordination mechanisms, aiding investors in aligning their actions and managing market complexities, thereby enhancing market stability. However, the reliability of these ratings is a topic of concern due to various influencing factors. Wang and Weitzner (2023) explore how the subjective beliefs of rating agencies influence credit markets. Their study finds that increased optimism among rating agencies leads to higher ratings and negative excess returns, prompting firms to increase leverage and investment.

Kisgen, Nickerson, Osborn, and Reuter (2020) emphasize that the experience and behavior of analysts significantly impact the accuracy of ratings. Credit rating analysts produce reports reflecting the issuer's ability by aggregating financial data, engaging with corporate executives, and processing information. In the presence of information frictions, persistent differences in analysts' abilities or perspectives can related to systematic and predictable differences in ratings. Fracassi et al. (2016) demonstrate that the subjectivity of rating analysts can significantly affect corporate bond prices, attributing 30% of the variation in corporate bond ratings to individual analysts. Various factors, including professional incentives, experience, and internal policies of the rating agencies, shape these analysts' behavior and decision-making processes. For instance, Kempf (2020) finds that analysts' career prospects motivate them to provide more accurate ratings, aligning with the "human capital formation" view. Cornaggia et al. (2017) also show that analysts' incentives and career paths influence their rating behavior and outcomes.

Traditional factors influencing rating accuracy include financial metrics such as profitability, leverage, and liquidity, alongside firm-specific characteristics like size and industry (Altman & Rijken, 2004; Blume, Lim, & Mackinlay, 1998; Hovakimian, Kayhan, & Titman, 2012). These metrics provide a quantitative basis for assessing the creditworthiness of issuers. Becker and Milbourn (2011) highlight the impact of competition among CRAs on rating quality, suggesting that increased competition can related to lower rating standards. Furthermore, Bongaerts, Cremers & Goetzmann (2012) investigate the value of having multiple credit ratings for a single security, revealing that additional ratings serve as certifications that can reduce information asymmetry and enhance the credibility of primary ratings.

Recent research underscores the importance of non-traditional factors, such as trust in financial relationships, in influencing rating accuracy. Trust affects the flow of information and communication effectiveness between stakeholders in the financial market. High levels of trust can related to more open and honest communication, thereby reducing information asymmetry and improving rating accuracy (Guiso et al., 2008). Conversely, a lack of trust can hinder the sharing of critical information, leading to inaccurate assessments and potential mispricing of credit risk. Bhagwat & Liu (2020) highlight the role of trust in information processing, demonstrating how trust impacts the accuracy of financial analysts' forecasts. Although their study focuses on security analysts, the findings are also relevant to understanding how trust might influence credit rating analysts.

We can better understand the elements influencing rating accuracy by examining traditional and non-traditional factors like trust. This holistic approach is essential for enhancing the reliability and credibility of credit ratings in financial markets.

2.2 Trust in Financial Relationships and Information Production

Trust is significant in financial relationships as it mitigates information asymmetry by facilitating better communication, leading to more accurate and reliable information. Akerlof's (1970) "lemons market" theory and Coleman's (1988) social capital theory emphasize that trust significantly lowers transaction costs and enhances market efficiency. Numerous empirical studies have shown that trust plays an essential role in financial decision-making (Guiso et al., 2008, 2009; Bhagwat & Liu, 2020; Hagendorff et al., 2023), mitigating the adverse effects of information asymmetry between corporate insiders and outsiders.

Higher levels of trust are associated with more transparent information sharing. Guiso et al. (2008) find that higher levels of trust in financial institutions and markets are related to greater participation in the stock market. Conversely, a lack of trust results in lower participation, negatively affecting market dynamics. They additionally point out that trust facilitated by cultural similarities enhances trade and investment. Higher bilateral trust levels are related to increased trade between countries by reducing transaction costs and mitigating the risks of opportunistic behavior (Guiso et al., 2009).

Moreover, Bottazzi et al. (2016) illustrate that trust is crucial in venture capital relationships. VCs are more likely to invest in early-stage ventures and provide more value-added services when they trust the entrepreneurs. Trust facilitates smoother interactions and better communication between VCs and entrepreneurs, leading to more effective monitoring and support. These findings support the theory that trust reduces financial market information asymmetry and transaction costs. The trust serves as an informal mechanism that complements formal contracts and legal protections.

Trust serves not only to mitigate information asymmetry but also significantly influences the process of information production and dissemination in financial markets. Signaling theory, articulated by Spence (1973), explains how managers use information to signal company quality to less informed parties, such as investors or analysts. Trust enhances the credibility and effectiveness of these signals, making them more reliable (Connelly, Certo, Ireland, & Reutzel, 2011). Empirical research supports this notion. For example, Anderson, Mellor & Milyo (2004) demonstrate that higher levels of trust within a community are related to more effective financial transactions and economic performance, thereby reinforcing the signals sent by managers. Similarly, Lins, Servaes & Tamayo (2017) find that trust in management positively affects firm value during financial crises, as trusted managers can better convey credible signals about the firm's stability and future prospects. These studies underscore trust's pivotal role in enhancing signals' reliability and effectiveness in financial markets. In the context of credit ratings, trust can improve the quality and accuracy of the information analysts produce.

The above literature highlights the importance of trust in reducing information asymmetry and enhancing the signaling quality during decision-making processes. However, Bae et al. (2023) examine the potential downsides of high levels of trust between the board of directors and the CEO. The study suggests that excessive trust may exacerbate agency problems. When the board trusts the CEO too much, it may related to insufficient oversight and monitoring. This lack of scrutiny allows the CEO to pursue personal goals or strategies that may not align with the best interests of the shareholders. The study underscores the complex role of trust in corporate governance, indicating that while trust is essential for effective collaboration and decision-making, too much trust can associated with negative outcomes by diminishing the board's monitoring effectiveness and exacerbating agency problems. This finding is particularly relevant for understanding the dynamics between CEOs and other stakeholders in financial decision-making contexts, such as credit ratings.

2.3 Hypothesis Development

Building on earlier discussions on credit ratings and the role of trust in financial relationships, this section examines the crucial role trust plays in enhancing rating accuracy.

According to signaling theory (Spencer, 1973), CEOs have strong incentives to reduce information asymmetry by signaling their firm's quality to market participants. This signaling often aims to secure better credit ratings and reduce financing costs. When CEOs trust analysts, they may share more sensitive or inside information, enabling analysts to develop a fuller understanding of the firm's operations, financial health, and strategic goals4. This comprehensive exchange can significantly enhance rating accuracy.

Based on the theoretical framework and fundamentals described above, we propose following hypothesis:

Hypothesis 1 (H_1): A higher level of trust from the CEO towards the RA is associated with more accurate credit ratings, assuming other factors remain constant.

While the CEO's primary motivation to release information to RAs is often driven by the need to maintain the company's reputation and interests, this incentive does not necessarily depend on the CEO's trust in a particular RA. As a result, even if the CEO does not fully trust an RA, information may still be provided out of necessity, reducing the direct role of trust in influencing how RAs handle and present this information.

In practice, RAs rely heavily on objective sources like financial reports (e.g., 10-K/10-Q) and regulatory disclosures (e.g., SEC filings) as core inputs, while also considering less formal signals such as the CEO's public statements, social media presence, or private communications. These types of information are sometimes ambiguous and subjective; however, trust can play a crucial role here by helping RAs view CEO-provided information as a more authentic reflection of the firm's quality (Connelly et al., 2011). When RAs trust the CEO's insights, verification costs are reduced, information flow is facilitated, and cooperation efficiency improves, potentially enhancing rating accuracy.

Therefore, we propose the hypothesis 2 from the RA's perspective:

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[4] The CEO transmits information to the rating analyst (RA) through various forms, such as financial statements, regulatory filings, public announcements, Management Discussion and Analysis (MD&A), conference calls, private communications, and social media. This is complemented by Moody's credit rating process, which begins with a pre-engagement stage where an introductory meeting or teleconference is conducted to outline the rating process to the issuer.

Hypothesis 2(H_2): A higher level of trust from RA towards the CEO is associated with more accurate credit ratings, assuming other factors remain constant.

Since RAs are responsible for gathering, processing, and analyzing information to produce credit ratings, their level of trust in the CEO directly influences how they interpret and present the CEO's information. A higher level of trust makes RAs more inclined to believe and accurately convey the CEO's insights, which enhances rating accuracy. In dynamic financial markets filled with complex and noisy data, RAs may often dismiss unverifiable information. However, when RAs trust the CEO, they are more likely to consider even ambiguous or incomplete insights with an open and inclusive approach. This trust enables RAs to recognize valuable signals that might otherwise be overlooked, ultimately contributing to more accurate credit ratings.

On the other hand, if analysts trust the CEO, they may be more willing to trust and accurately convey the information provided by the CEO, reducing misjudgements caused by doubts about the veracity of the information. From the perspective of communication, trust can facilitate effective communication between two parties. The relationship of trust between the CEO and the analyst helps reduce communication barriers and enables both parties to more accurately understand each other's views and needs, which helps the analyst to more accurately interpret the company's operational and financial data, and also encourages the analyst to more actively seek feedback and opinions from the CEO during the rating process, thus further improving the accuracy of the rating.

At the same time, the trust relationship helps reduce the bias and conflict of interest in the rating process. When the CEO and the analyst trust each other, they may be more willing to treat the rating work in an objective and fair attitude, and avoid the rating distortion caused by personal bias or interest drive, external pressure (such as expectations from investors, competition from peers, etc.). Thus, we propose the hypothesis 3:

Hypothesis 3 (H_3): A high level of mutual trust between the CEO and RA is associated with more accurate credit ratings, assuming other factors remain constant.

Mutual trust between the CEO and the RA creates an efficient platform for exchanging key information, enabling both parties to share and receive critical insights openly. This full exchange allows analysts to gain a comprehensive understanding of the company's operations, financial position, and potential risks, forming a strong foundation for accurate credit evaluation. Additionally, mutual trust reduces misunderstandings and conflicts, as both parties are more likely to communicate cooperatively, minimizing rating biases that could arise from miscommunication. Over time, this trust fosters long-term collaboration, encouraging both the CEO and RA to consider the company's long-term goals, historical performance, future strategy, and market conditions — factors essential for improving the accuracy and forward-looking quality of credit ratings.

While trust can potentially improve rating accuracy by facilitating better information exchange, its impact may vary depending on the specific scenario and the perceived quality of the information environment. In subsequent empirical analyses, we will test both hypotheses to disclose the complex relationship between trust and credit rating accuracy in financial markets.

3. Data and Methodology

3.1 Data Description and Sample Selection

In this section, we first describe the data sources, followed by the data filtering process, and conclude with the construction of the final sample.

First, the bond issuance and rating data are obtained from the Mergent Fixed Income Securities Database (FISD), which provides detailed information on bond issuances, including issuance dates, issuer details, ratings from Moody's and S&P, and subsequent rating updates. Using these information, we are able to construct our key variable, *Rating Inaccuracy*, defined as the absolute difference between Moody's initial rating and its subsequent revision within one year, as discussed in Section 3.2.

Second, trust scores are derived from the Eurobarometer survey data, which has conducted public opinion surveys across European Union (E.U.) member nations since 1970, expanding its coverage from five countries in 1970 to 16 by 1996. These trust measures are linked to individuals' countries of origin based on surnames, following the methodologies of Bae et al. (2023), Hagendorff et al. (2023), and Bhagwat & Liu (2020).

Third, Rating analyst (RA) information is manually collected from Moody's official website. This process represents a key contribution of the study, as we developed a web scraper to gather and analyze each rating-related announcement on Moody's website. The extracted data includes issuer details, analyst full names, positions, office locations, report lengths, and the frequency of keywords relevant to our model.

Finally, CEO information and firm-level financial data are sourced from the BoardEX database and Compustat, respectively. Cultural data is obtained from Hofstede's cultural dimensions, and additional data is collected from *Ancestry.com* for matching surnames to origin countries. Gender information for both rating analysts and CEOs is retrieved from *Genderize.io*. For additional tests, we also use media coverage data from the Raven Pack database, analyst coverage from the I/B/E/S database, and geographical distance and flight time data from Google API and OpenSky Network.

The rating announcement data is collected from Moody's official website, which categorizes announcements into four types: Announcement, Rating Action, Assessment Announcement (since 2021), and Announcement of Periodic Review. Due to data availability constraints before 2021, we focus exclusively on U.S. firms and include only the "Announcement" and "Rating Action" types. We retained market segments such as corporates, financial institutions, and insurance; while excluding segments like infrastructure, funds, sovereigns, structured finance, and public finance due to their distinct characteristics.

To ensure robustness in the sample, we exclude bond issues associated with more than four entities, unless these entities are related (e.g., parent and subsidiary companies). Moody's rating reports can sometimes apply to a single company, but in other cases, they may cover multiple companies. To address this, we first manually clean and group the companies in our sample, treating parent and subsidiary companies as a single entity when appropriate. If a rating report is issued for more than four companies, we classify it as an industry-level report rather than one specific to a particular issuer, and therefore exclude it from the sample.This approach follows the methodology of Kisgen et al. (2020), which deemed reports as firm-specific if linked to fewer than four entities.

Bonds with unique features such as asset-backed, puttable, exchangeable, convertible, private placement, and sinking fund bonds are also excluded to maintain consistency. Since callable bonds make up a large portion of the market, excluding them would lead to a significant bias in the sample. To account for the callable feature, a dummy variable is created and included in the regression analysis to control for its potential effects.

The sample period for this study covers bond-issue-level observations from the first quarter of 2000 to the second quarter of 2023. The final sample comprises 10,832 bond issuances by 916 firms in the U.S. primary bond market. We restricted our analysis to U.S. companies to maintain consistency and relevance to the U.S. bond market. Our study also focuses on initial bond ratings (bond IPOs), hypothesizing that trust is more critical when RAs and CEOs are less familiar with each other.

Moody's announcements sometimes provide office locations, which we use to calculate geographical distances. However, these data are not included in the baseline regression due to limitations. Our sample shows that the most rating analyst offices are located in New York City (NYC), which accounts for over 90% of the data, followed by Frankfurt and Toronto, with some based in London, Hong Kong, Sydney, and Tokyo.

3.2 Rating Inaccuracy

Traditional metrics of rating accuracy, such as average default rates by rating category or accuracy ratios, rely on a large number of sample events to be meaningful (Cornaggia et al., 2017). However, given that an analyst only rates a limited number of securities or bonds in each period and defaults are infrequent events, these measures may not reliably gauge analyst-level performance. Instead, to measure rating inaccuracy, we follow Kempf (2020), who suggests that credit ratings represent a publicly observable and relatively frequent measure of output by individual analysts; in addition, that subsequent corrections of initial ratings issued by these analysts provide a useful proxy for analyst (in)accuracy. The formula for inaccuracy is:

$$Inaccuracy\_level_{j,\mathrm{t}} = \frac{1}{N-1}\sum_{k=1}^{N-1} \left|R_{j,t_k} - R_{j,t_0}\right|$$

where N represents the total number of ratings assigned to bond j over a given period, starting from time t_0 (the initial rating), and includes all subsequent upgrades or downgrades within one year. The term $N-1$ ensures that the initial rating is not counted in the average calculation of inaccuracy. R_{j,t_0} is the initial rating of bond j at the beginning of the period, and R_{j,t_k} represents the updated ratings for bond j within the period extending up to $t + h$, where h is equal to one calendar year.

For example, as shown in the figure, suppose bond j initially receives a Moody's rating of Aa3 on January 15, 2016. The rating is then subsequently adjusted three times within the same calendar year: upgraded to Aa2 on January 20, downgraded to Baa1 on February 8, and further upgraded to Aa1 on February 26. The *Inaccuracy* is then calculated as the average of the absolute differences between the initial rating and the subsequent ratings:

$$Inaccuracy = \frac{1}{4-1}(1 + 4 + 2) \approx 2.33$$

This inaccuracy measure captures deviations in ratings over time, providing a robust proxy for assessing the accuracy of the initial ratings assigned by analysts. Bonds that experience a change in either the CEO or RA between time t and $t+h$ are excluded from the sample to maintain consistency in the analysis.

Moreover, Moody's organizational structure supports the reliability of this approach. Specifically, having a separate internal surveillance team perform the subsequent rating adjustments ensures these changes are not influenced by the same analyst who initially assigned the rating (Kempf, 2020). This institutional feature lends additional credibility to using subsequent corrections as a measure of inaccuracy.

The credit rating process at Moody's begins with a pre-engagement stage, where an introductory meeting or teleconference is conducted to outline the rating process to the issuer. Following this, an analytical team is assigned to the issuer, led by a "Lead Analyst," who begins the analysis by gathering both financial and non-financial information[5]. During this data collection stage, issuers are asked to provide comprehensive information, which is then analyzed by the lead analyst. The analyst also engages in open discussions with the issuer regarding credit strengths and weaknesses before making a recommendation to a rating committee. Once the rating committee reaches a decision, the assigned rating is communicated to the issuer and subsequently made public.

After the initial rating is assigned, the final stage involves the ongoing surveillance of the credit rating. This surveillance is carried out by a separate team within Moody's, ensuring that ratings are periodically reviewed and adjusted as necessary, at least once every twelve months, to maintain accuracy and objectivity (Moody's Investors Service). This separation of responsibilities between the initial rating assignment and subsequent surveillance provides an added layer of credibility when using subsequent rating corrections to measure inaccuracy.

[5] Moody's rating reports typically have one or most two analysts listed. We consider the first or sole listed analyst as the 'lead analyst.' Unless otherwise specified, the RA mentioned in this paper refers to the lead analyst.

3.3 Measuring Trust from RA to CEO

To measure the level of trust from rating analysts to CEO on rating accuracy, we first need to quantify the trust level. We utilize the Eurobarometer survey data to measure trust between countries, following the methodologies established by Guiso et al. (2009) and extended by Bae et al. (2023). The Eurobarometer surveys, conducted annually for the European Commission since 1970, provide extensive data on European Union citizens' social and political attitudes. Our trust measures are derived from Eurobarometer survey waves from 1990 to 1996, focusing on responses to the question: "I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you have a lot of trust, some trust, not very much trust, or no trust at all." Responses are scored from 1 to 4, with 1 being "no trust at all" and 4 being "a lot of trust." Using responses from 1990 to 1996, we construct a trust matrix between 16 European countries and extend it to include 27 countries, following Bae et al. (2023).[6]

To link trust scores between RAs and CEOs, we determine the most likely origin countries for their surnames using data from *Ancestry.com*, following the approaches of Bae et al. (2023), Hagendorff et al. (2023), and Bhagwat & Liu (2020).[7] For each RA and CEO, we identify the three countries with the most frequent origins associated with their surnames and then link them to their trust level. Once the origin countries are determined, we calculate the trust score from RA *i* to CEO *j* using the formula:

$$Trust_{i \to j} = \sum_{C1=1}^{3} \sum_{C2=1}^{3} P_{i,C1}\, P_{j,C2} Trust_{C1 \to C2}$$

where $P_{i,C1}$ and $P_{i,C2}$ represent the probabilities of countries $C1$ and $C2$ being the origin countries of RA i and CEO j, respectively, and $Trust_{C1 \to C2}$ represents the level of trust that citizens of country $C1$ have in citizens of country $C2$. This comprehensive approach ensures that multiple origin countries and their respective trust levels are incorporated into the trust measure; it also mimics the process when people get in touch and assess the origins based on names.

[6] The Eurobarometer has conducted public opinion surveys in European Union (EU) member nations since 1970, with coverage increasing to 16 countries by 1996. The participants in a survey from 16 European countries include France, Belgium, the Netherlands, Germany, Italy, Luxembourg, Denmark, the U.K., Ireland, Greece, Spain, Portugal, Norway, Sweden, Finland, and Austria. The respondents are questioned about the impact on other non-European countries included in the survey are China, Russia, Japan, Switzerland, Turkey, Bulgaria, Romania, Hungary, Poland, Slovenia, and the Czech Republic (Slovakia).

[7] https://www.ancestry.com/search/collections/7488

To implement this measure, we first matched the surnames of RAs and CEOs to their probable countries of origin using historical immigration records from the Ancestry.com website. Following the example of Pan, Siegel & Wang (2017), based on the names and ethnicities of immigrant passengers and their countries of origin in immigration records from foreign ports to New York City from 1820 to 1957, our study manually constructed a surname-oriented database to determine the cultural origins of our study participants.

Selecting *Ancestry.com* as the source to determine the cultural origin of the study subjects has a distinct advantage. The large enough database supports the research use of the origin distribution of all immigration passenger records with the same surname to infer the true origin country of the surname.[8] For example, in our database, 54.09% of the subjects with the surname Lavin are from Ireland, followed by 18.08% from Spain, 15.96% from the United Kingdom, and the rest from other countries or regions. Constructing a database based on *Ancestry.com* allows us to calculate different proportions of country origins by distribution rather than simply the average of two or more origin countries.

Next, we obtained the probabilities of these origins and linked them to the corresponding trust scores from the Eurobarometer surveys. A country missing from Eurobarometer surveys is excluded from calculating trust scores. We manually collected data on RAs and CEOs from Moody's official website, focusing on announcements signed by RAs. Typically, these announcements list one to two RAs. We define the primary RA as the first or most senior RA listed, as this individual is presumed to be dominant in the decision-making process. Our baseline regression considers only the primary RA, but additional test include secondary RA and Chief Financial Officers (CFOs).

3.4 Research Design

We employ regression models to analyze the impact of trust between RAs and CEOs on rating accuracy. The baseline regression model is specified as follows:

$$Inaccuracy_{j,t} = \alpha + \beta Trust_{RA,CEO_{i,t}} + Trust_{CEO,RA_{i,t}} + X_{j,t} + Y_{i,t-1} + Z_{RA,CEO_{i,t}} + \gamma_{Year} + \delta_{Firm} + \phi_{RA} + \epsilon_{j,t}$$

[8] It is worth mentioning that ethnicity/nationality are very detailed in the *Ancestry.com* records. For example, Germany is usually distinguished as East Germany and West Germany; Ireland is also recorded as Southern Ireland and Northern Ireland. To match surnames with Hofstede's cultural indices for this paper, we combine related regions and calculate them uniformly as one country. Multiple religion-related countries are also counted uniformly, such as Muslim countries. However, some countries are classified into multiple units because of their special national conditions; China, Hong Kong, and Taiwan are separate regions in the research.

where j refers to bonds and i refers to issuers. The dependent variable, $Inaccuracy_{j,t}$, represents the absolute difference between the initial bond rating assigned by Moody's and the subsequent updated rating within one year. This measure captures the deviation in the ratings over time, thus serving as a proxy for rating accuracy. The key independent variable $Trust_{RA,CEO}$ is the trust score from the rating analyst to the CEO. Additionally, we include the $Trust_{CEO,RA}$ that is the trust score from the CEO to the rating analyst in all models, since trust is a bidirectional measure. This means we not only evaluate how much the RA trusts the CEO but also consider how much the CEO trusts the RA. We also include the three different fixed effects, $\gamma_{Year}, \delta_{Firm}, \phi_{RA}$ represent the year, firm, and rating analyst fixed effects.

The control variables are grouped into three categories: bond-level, firm-level, and pair-level controls. Bond-level controls at quarter *t*, which include Moody's *Bond Rating*, measured on a scale where AAA=21, AA+=20, ..., CCC-=3, CC=2, DDD and lower =1; *Ln(No. of Issuance)*, the logarithm of 1 plus the firm's issuance experience in the primary market over the sample period (2000-2023); *Ann.Type* represent the dummy variable equals to 1 for rating action announcements and 0 for other types of announcements; The *R144A* status is a dummy variable equal to 1 if the bonds are type R144A and 0 otherwise. *Callable* status is also included as a dummy variable, equal to 1 if the bonds are callable and 0 otherwise.

Firm-level controls at quarter $t-1$ include *Size*, *Profitability*, *Leverage*, *Market-to-book ratio* (*MTB*), and *Tangibility*. *Size* is measured as the natural logarithm of net sales adjusted for inflation to the year 2000. *Profitability* is the operating income before depreciation scaled by the book value of assets. *Leverage* is calculated as the sum of long-term debt and short-term debt minus cash and cash equivalents, divided by the book value of assets. The *market-to-book ratio* (*MTB*) is the market value of total assets scaled by the book value of assets. *Tangibility* is measured as net property, plant, and equipment scaled by the book value of assets.

Pair-level controls between the primary RA and CEO include *Dif.Gender* and *Dif.Cultural*. *Dif.Gender* is a dummy variable equal to 1 if the CEO and the RA are of different genders and 0 if they are of the same gender. *Dif.Culture* is the average cultural distance score between RA and CEO. Following Bae et al. (2023), *Dif.Culture* is calculated as the average weighted cultural distance between the RA and CEO, using Hofstede's (2010) six cultural dimensions (IDV, UAI, PDI, MAS, LTO, IVR).[9]

These control variables help account for various factors that might influence rating accuracy, ensuring that the impact of trust is isolated and accurately measured.

3.5 Summary Statistics

Table 1 provides summary statistics for the bond-issue-level observations in our sample. The key variable, *Inaccuracy*, measured as the absolute difference (in notches) between Moody's initial bond rating and the revision rating within one year, has a mean value of 0.016 with a standard deviation of 0.161, showing that most bond ratings in our sample are quite accurate. $Trust_{RA,CEO}$ variable is standardized with a mean of 0 and a standard deviation of 1, reflecting a range from -6.771 to 2.606. $Trust_{CEO,RA}$ variable is standardized with a mean of 0 and a standard deviation of 1, reflecting a range from -8.319 to 2.795.

Bond Rating includes the average bond rating of 16.65, with most ratings clustering around the higher end of the scale, as indicated by a median of 17, which is equal to Moody's rating level A+. The *Ln(1+No. of Issuance)* show means 5.365, highlighting the distribution of the firm's issuance experience. The average value of *Ann.Type* is 0.858, with a variance of 0.349. Within our sample, approximately 8.4% of the bonds are classified under Rule 144A, which means these bonds can be traded among Qualified Institutional Buyers (QIBs) without SEC registration.[10] While Callable bonds represent 98.7% of the

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[9] *Diff.Culture* is calculated as the average weighted cultural distance between the RA and CEO, using Hofstede's (2010) six cultural dimensions (IDV, UAI, PDI, MAS, LTO, IVR). Hofstede's cultural dimensions are widely used in academic research to understand the effects of culture on various economic and financial behaviors. These dimensions include Individualism versus Collectivism (IDV), Power Distance Index (PDI), Uncertainty Avoidance Index (UAI), and Masculinity versus Femininity (MAS). The framework provides a systematic approach to quantifying cultural differences, which can significantly influence business practices, management styles, and investor behavior. The robustness and comprehensive nature of Hofstede's dimensions have made them a valuable tool in cross-cultural studies, facilitating the comparison of cultural impacts across different contexts and countries. In finance, these cultural dimensions help explain variations in corporate governance, investment decisions, and market reactions across different cultural settings (Chui, Lloyd, & Kwok, 2002; Aggarwal, Kearney, & Lucey, 2012; Eun, Wang, & Xiao, 2015).

[10] Rule 144A allows qualified institutional buyers (QIBs) to trade debt securities without the requirement for registration and review by the Securities and Exchange Commission (SEC). This provision substantially

sample, as indicated by the mean value of 0.987.

Firm-level characteristics include *Profitability*, *MTB*, *Tangibility*, *Leverage*, and *Size*. We observe that the average profitability, measured as operating income before depreciation scaled by the book value of assets, is relatively modest at 2.3%. This implies that the firms generally exhibit moderate operating efficiency and financial health levels. The market-to-book ratio (*MTB*) averages 1.45, meaning that the market values these firms slightly higher than their book value, showing a positive but not overly optimistic view. The average *Tangibility* is 0.163, *Leverage* is 0.551, and the natural logarithm of net sales (*Size*) averages 5.691. This implies that the firms in our sample have a relatively small portion of tangible assets, moderate debt levels, and are generally large, possibly including many established companies.

Pair-level characteristics are represented as *Dif.Cultural* and *Dif.Gender*. The variable *Dif. Cultural*, which measures the average cultural distance score between the RA and CEO using Hofstede's cultural dimensions, has a mean of 0. This suggests that there is significant cultural diversity among the CEO-RA pairs, which may affect their interactions and the accuracy of ratings. The variable *Dif.Gender* shows that approximately 47.5% of the CEO-RA pairs in our sample are of different genders. This diversity in gender pairings is important because it can influence the trust and communication dynamics between the CEO and the rating analyst.

4. Empirical Results

4.1 Trust and Rating Accuracy

To examine the how trust affects rating accuracy, we estimate baseline OLS regression model. The results in Table 2 consistently show a significant negative association between trust and *Inaccuracy* across all models. This suggests that higher trust from the rating analyst to the CEO is associated with lower rating inaccuracy, indicating greater rating

increases the liquidity of these securities, making them more attractive and potentially less risky for institutional investors.

accuracy. We discuss the results column by column to provide a deeper understanding of the findings.

The Eurobarometer survey's strength lies in its bidirectional trust measurement, allowing us to observe how trust in both directions influences outcomes. Column 1 focuses solely on trust from CEOs to rating analysts ($Trust_{CEO,RA}$). In this case, the coefficient for is -0.031 and is highly significant (t-statistic = -1.999) demonstrate that when CEOs trust rating analysts more, the lower the inaccuracy of the rating; implies they are likely to share more comprehensive and detailed information to their trusted analyst. This increased transparency helps the RA in their analysis, resulting in more accurate ratings. Column 2 shifts the focus to the trust from rating analysts to CEOs ($Trust_{RA,CEO}$). Since the rating report is written by the RA, their level of trust in the CEO significantly impacts how they incorporate the information provided by the CEO. The coefficient is -0.029 and is highly significant (t-statistic = -2.221) in Column 2 shows that the more an RA trusts the CEO, the more likely they are to integrate the CEO's inputs effectively, thus improving rating accuracy.

The question of which trust direction matters more is an empirical question. Column 3 considers both direction of trust simultaneously to determine which direction of trust plays a more critical role. In Column [3], the coefficient for $Trust_{RA,CEO}$ is -0.014 and is highly significant (t-statistic = -2.102). But the coefficient of $Trust_{CEO,RA}$ is not significant. The results indicate that that RA's trust in CEO has a greater impact on credit rating when both CEO's trust in RA and RA's trust in CEO are considered. This is likely due to two primary reasons: (1) The rating report is authored by the RA, making their confidence in the CEO crucial for incorporating accurate information. (2) CEOs are motivated to release information to all RAs to seek favorable ratings and reduced financing costs, but *RA trust in the CEO* directly impacts how much of this information is credibly utilized. Moreover, the RA's independent judgment and their inclination to trust the CEO are pivotal because RAs need to decide whether the CEO's inputs are reliable enough to influence the final rating.

The economic significance behind the observed effect in Column 3 can be quantified by examining the standard deviation of *Inaccuracy* . In column [3], the coefficient for $Trust_{RA,CEO}$ is -0.014. To measure the impact, we divide this coefficient by the standard deviation of *Inaccuracy*, which is 0.161, resulting in a value of approximately -0.087. This result suggests that for each one-unit increase in $Trust_{RA,CEO}$, the rating *Inaccuracy* decreases by 0.087 standard deviations on average. This implies that trust from the RA to the CEO has a measurable and meaningful impact on improving rating accuracy. Given the empirical findings from Columns 1 to 3, our baseline model includes $Trust_{RA,CEO}$ as the primary variable of interest, while $Trust_{CEO,RA}$ is included as a control variable. This reflects the greater importance of the RA's judgment in the rating process and how their perception of the CEO's credibility can directly impact rating outcomes.

On the basis of Column 3 in Table 2, the intersection term $Trust_{RA,CEO} \times Trust_{CEO,RA}$ is added for Column [4] and the regression is carried out together. This interaction term captures the effect of mutual trust between RAs and CEOs. The coefficient for $Trust_{RA,CEO} \times Trust_{CEO,RA}$ is -0.023 and is highly significant (t-statistic = (-1.976) remained significant, while $Trust_{CEO,RA}$ and $Trust_{CEO,RA}$ were not significant. This shows that the mutual trust between the CEO and RA plays a critical role in improving rating accuracy.

When both the CEO and the RA have high levels of trust in each other, it fosters an environment where the information shared is more reliable, and the RA feels more confident in using this information effectively. The significance of the interaction term underlines the combined strength and importance of mutual trust. When mutual trust is present, it results in more accurate ratings due to better quality information exchange and interpretation.

In all specifications from Column [1] to Column [4], we include all the bond, firm and pair level control characteristics and fixed effects for the firm, year, and rating analyst to control for unobserved heterogeneity that could affect our results. This inclusion helps to ensure that our results are not driven by time-invariant firm characteristics, year-specific effects, or analyst-specific factors (Petersen, 2009; Gormley & Matsa, 2014). The adjusted R-squared values range from 0.441 to 0.447, indicating a reasonable fit of the models to the data (Roberts & Whited, 2013).

In summary, our baseline results show that when rating analysts trust the CEO more, the credit ratings are more accurate. This finding stays true even when we consider the CEO's trust in the rating agency (RA) and the mutual trust between them. This section highlights how trust is essential for improving credit ratings' accuracy, providing a strong foundation for future in-depth analyses.

4.2 Mechanism Test

In this section, we explore the mechanism test, specific use of information quality, RA ability, and the RA effort, are used as analytical tools to explore whether and how they affect RA's trust in CEOs, and to further judge the effect of such trust on the accuracy of credit ratings. Through this careful analysis, we wanted to shed more light on the complex interactions between trust relationships and information quality, RA ability and the RA effort, and the paths and effects of them on the accuracy of credit rating.

4.2.1 Information quality

If trust determines how analysts use signals received, then it should affect reducing rating error only when the signals are generally faithful. In other words, if information is generally misleading, high trust may lead to lower rating accuracy. Therefore, we test whether the effect of trust on rating accuracy is conditional on good information quality.

Table 3 examines how managerial information quality affects the trust-rating accuracy relationship. Columns [1] and [2] report the results of cross-sectional tests for two managerial information quality characteristics: Accruals and Restatement. Accruals are calculated using the Kothari Model, which matches firms based on performance metrics such as Return on Assets (ROA). In Column [1], the interaction between $Trust_{RA,CEO}$ and

Accruals is significantly positive (0.149, t-statistic = 1.733). These results suggest that trust from the RA to the CEO might be less effective or counterproductive in firms with higher discretionary accruals, indicating lower-quality financial reporting. The increased difficulty in discerning true managerial intent and financial health may lead RAs to over-rely on potentially manipulated information, resulting in inaccurate ratings. Restatement, defined as the number of fraud restatements of the firm in the year before the rating release, is analyzed in Column [2]. The interaction term $Trust_{RA,CEO}$ ×Restatement is also significantly positive (0.056, t-statistic = 1.797). This indicates that in firms with a history of fraud, $Trust_{RA,CEO}$ increases rating inaccuracy.

The findings in Table 3 emphasize the importance of management information quality in evaluating the impact of trust on rating accuracy. Signaling theory (Spence, 1973) emphasizes that in markets with asymmetric information, the party with the information advantage (e.g., management) sends signals to convey information about its quality or value to the party with inferior details (e.g., investors and analysts) (Akerlof, 1970; Healy & Palepu, 2001; Graham et al., 2005). However, when the information provided by management is of low quality, these signals may no longer be reliable and may even be manipulated to mislead recipients (rating analysts). The manipulation of accruals or the existence of a history of financial restatements, which are evidence of a company's low quality of financial reporting, can be seen as "distorted" signals that complicate the information environment. These distorted signals make it harder for RAs to distinguish between genuine and manipulated information, compounding information asymmetries (Dechow et al., 1995). Thereby, the rating analysts' trust in the CEO fails to enhance rating accuracy when poor quality information is provided by management. In these cases, the RA's trust in the CEO may exacerbate the inaccuracy of the rating rather than enhance its accuracy. Therefore, our study emphasizes the importance of considering the quality of management information as a critical factor in assessing the impact of trust on rating accuracy.

4.2.2 RA ability

Table 4 reports the results of how the information production capacity of rating analysts affects RA's trust in CEOs and the accuracy of bond ratings. Columns [1] and [2] report the results of cross-sectional tests for three different rating analyst ability characteristics: *RA Seniority* and *RA Experience*. *RA Seniority* is a dummy variable indicating the seniority of Moody's rating analysts. It equals 1 for senior positions (corresponding to Senior Vice President and Managing Director) and equals 0 for junior to mid-level positions (corresponding to Analyst, Senior Analyst, and Senior Credit Officer). *RA Experience* is the number of reports written by Moody's rating analysts during the sample period from 2000 to 2023, divided by 100.

As can be seen from the table, the coefficient of $Trust_{RA,CEO} \times$ *RA Seniority* is -0.036 and significant at 5% level (T-value =-2.359). $Trust_{RA,CEO} \times$ *RA Experience* coefficient is -0.009 and significant at 1% level (T-value =-1.862). This indicating that the information production capacity of RA has a positive impact on the effect of trust to improve the accuracy of bond rating. The expertise and deep experience of analysts enable them to more accurately interpret and analyze financial data, market conditions and industry trends of companies, thereby developing more accurate credit ratings. When investors see analyst ratings, they are more likely to trust those made by experienced and competent analysts, because these analyst ratings are often more closely related to the true credit status of the company. At the same time, the ability of analysts is also reflected in their ability to process complex information and respond to market changes. In a rapidly changing market environment, analysts need to quickly capture and interpret new information and adjust their ratings accordingly. More competent analysts are often more sensitive to market movements, so they can make timely revisions to their ratings, ensuring that the results are always in line with the company's credit profile. This ability to dynamically adjust not only improves the timeliness of ratings, but also further enhances investor trust in ratings, thus improving the accuracy of credit ratings.

At the same time, it can also be found from the regression results that compared with RA experience, RA qualifications have a more significant positive effect on improving the accuracy of the rating report. The reason why RA seniority plays a more obvious role than RA experience in enhancing RA's trust in the accuracy of the rating report is that seniority often represents the comprehensive embodiment of the analyst's status, experience and professional knowledge accumulation in the rating industry. Analysts in senior positions, such as senior vice presidents and managing directors, typically have longer careers, broader industry horizons, and deeper professional insights. This qualification allows them to take a more holistic view of a variety of factors when assessing a company's credit standing, and thus more accurately judge the competence and integrity of the CEO. As a result, when analysts in senior positions trust CEOs, their ratings reports tend to be more accurate and reliable. Second, while RA experience is also an important measure of an analyst's ability, it is more a reflection of the amount of work and practice an analyst has accumulated over a specific time period. Qualifications, by contrast, are more focused on the growth and development of the analyst throughout their career. Analysts in senior positions have typically experienced more challenges and trials in their careers, which allows them to analyze and judge more calmly and comprehensively in the face of complex situations. Therefore, seniority may have a higher weight on the impact of trusting CEOs on the accuracy of rating reports, as it represents not only the analyst's experience and practical accumulation, but also their professionalism and comprehensive competence.

4.2.3 RA Effort

This section uses the RA Effort to test the mechanism, and the results are reported in Table 5. How hard an analyst works directly affects the amount of information they are able to collect, analyze, and interpret, which is critical to forming accurate ratings. A high-effort analyst may conduct more in-depth research to assess the value of the company from more angles, thus improving the accuracy of the rating. How hard analysts work also affects their ability to combat bias and cognitive error. In the face of the bias that a high level of trust in a CEO can bring, a diligent analyst is more likely to conduct a more nuanced analysis to uncover potential negatives and thus adjust his rating to be more accurate.

Columns [1] and [2] in Table 5 analyze two metrics of rating analyst effort: *Word Count* and *Data Keywords*. *Word Count* is calculated as the logarithm of one plus the total word count of the full text in reports produced by the rating analyst. *Data Keywords* is calculated as the logarithm of one plus the count of specific terms related to data, metrics, indicators, instruments, and quantitative or qualitative descriptors. From the results in Table 5, it can be found that the coefficient $Trust_{RA,CEO}$ and *Word Count* is 0.068 and significant (T-value is 2.374), and the coefficient with *Data Keywords* is 0.089 and significant (T-value is 1.995). It shows that RA's trust in CEO can significantly improve rating analyst's effort level. When RA trust the CEO, they are more likely to trust the information provided by the CEO to be accurate and reliable, which reduces their workload in information gathering and verification, allowing them to devote more time and energy to in-depth analysis and understanding of the company's operations and financial health. It stands to reason that when the RA trusts the CEO, the CEO's company will attract more attention from the RA, which will prompt the RA to devote more energy to writing the analysis report (Harford et al., 2019). Therefore, the trust relationship promotes a positive work attitude among analysts, making them more willing to put in extra effort to provide more accurate and in-depth rating reports. At the same time, RA's trust in the CEO is also reflected in the CEO's leadership ability and the company's strategic decisions. When analysts believe the CEO can lead the company to long-term growth and success, they are more likely to be optimistic about the company and willing to put more effort into writing accurate and comprehensive rating reports. This trust not only motivates analysts to work, but also drives them to understand the company more deeply in order to more accurately assess its credit profile and future prospects. Therefore, RA's trust in the CEO can significantly improve RA's effort level, thus improving the accuracy and reliability of rating reports.

4.3 Mitigate endogeneity issue

To ensure the robustness of our results, we conducted several additional tests to address potential concerns. First, we considered endogeneity issues by incorporating additional control variables to account for omitted variable bias. Second, we examine whether a change in CEO leads to the departure of a Moody's RA to examine reverse causality and thus address possible endogeneity issues. These robustness checks collectively reinforce the reliability and validity of our findings.

4.3.1 Omitted Variable & FEs

To alleviate omitted variable bias concerns, Table 6 incorporates additional controls effects to validate the robustness of our findings.

In Column [1], we included six dimensions of cultural distance based on Hofstede's cultural dimensions: *Cultural Distance PDI* (Power Distance Index), *Cultural Distance IDV* (Individualism vs. Collectivism), *Cultural Distance MAS* (Masculinity vs. Femininity), *Cultural Distance UAI* (Uncertainty Avoidance Index), *Cultural Distance LTO* (Long-term orientation vs. Short-term orientation) and *Cultural Distance IVR* (Indulgence vs. Restraint) (Hofstede, 1984, 2010). All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. After controlling for *Cultural Distance*, the regression results are still significant.

Column [2] introduces two additional RA characteristics: *RA Seniority* and *RA Experience*. Despite including RA fixed effects, these variables capture time-varying aspects of the RA's career. The coefficient for $Trust_{RA,CEO}$ remains negative and significant (-0.015, t-statistic = -2.116), confirming that our findings are not driven by variations in analysts' characteristics.

In Column [3], we included CEO fixed effects to control for CEO-specific heterogeneity. The coefficient of $Trust_{RA,CEO}$ remains significantly negative (-0.014, t-statistic = -2.003), indicating that the trust effect persists even when accounting for unobserved CEO characteristics.

These robustness checks confirm that our results are stable and reliable, addressing potential endogeneity concerns and reinforcing the credibility of our findings.

4.3.2 Endogeneity Issue

Table 7 presents endogeneity test results to examine whether changes in CEOs lead to turnover among RA at Moody's. The dependent variable, *RA Turnover*, in Columns [1] and [3], captures changes in the assigned rating analyst. The key independent variable,

$Trust_{RA,CEO}$, in Columns [2] and [4], is a standardized measure of the trust level from Moody's rating analyst toward the CEO.

Columns [1] and [2] use a one-year lag (i.e., CEO death in year $t-1$ and RA turnover in year t), while Columns [3] and [4] use a two-year lag (i.e., CEO death in year $t-2$and RA turnover in year t). *CEO Exogenous* is a binary variable set to 1 if the CEO died while in office without the option to resign due to health reasons and 0 otherwise. This variable serves as an exogenous shock, testing the causal impact of CEO turnover on RA turnover.

It can be seen from the results in Table 7 that *CEO Exogenous* effects on *RA Turnover* and$Trust_{RA,CEO}$ are not significant, indicating that there is no reverse causality in the process of trust affecting the accuracy of rating reports. The insignificance of columns [1] and [3] indicates that the change in the assigned rating analyst is not significantly affected by the exogenous effect of CEO. This means that the CEO change was not a major factor in the departure of Moody RA. In other words, Moody's does not appear to have deliberately adjusted its team of rating analysts based on a change in CEO, thus ruling out the possibility that the company intentionally assigned RA's related to CEO trust for a specific purpose, such as improving rating accuracy. Further, the non-significant results in columns [2] and [4] suggest that the standardized measure of trust in CEOs by Moody's rating analysts is not significantly affected by the exogenous effect of CEOs. This finding further reinforces our conclusion that there is no reverse causation: Moody's RA's level of trust in CEOs is not driven by a change in CEO. Therefore, we can be confident that there is no reverse causality between the departure of Moody's RA and the change of CEO in the context of this study, which provides a solid evidence base for us to accurately interpret and evaluate the relationship between the two. This shows that there is no endogeneity problem in the result of main regression, and it is robust.

4.4 Additional Analysis

4.4.1 Distance & External Information

(1) Distance

If trust is indeed a substitute for verifying signals, then trust should be less valuable when there is more approach to verifying signals (i.e., information production difficulty). For example, if analysts are close friends with CEOs, they don’t need to rely on their trust level to determine whether to accept a signal or not – they can simply ask their CEO friend during a dinner conversation. While personal connections are hard to measure, we proxy the information production difficulty by geographical distance. It is comprehendible and well-documented that when people are more geographically closed, the information asymmetry reduces (Levine, Lin, Peng, & Xie, 2020; Chen, Ma, Martin, & Michaely, 2022).

Table 8 investigates how geographical factors, which contribute to the difficulty of information production, interact with trust to affect rating accuracy. Columns [1], [2], and [3] report the results of cross-sectional tests for three different information production difficulty characteristics: *Geographical Distance*, *Flight Distance*, and *Flight Time*. *Geographical Distance* is the logarithm of 1 plus the distance (in km) between the CEO and RA offices, calculated using the Haversine formula based on their latitude and longitude coordinates. In Column [1], the interaction term $Trust_{RA,CEO}$ × Geographical Distance is significantly negative (-0.006, t-statistic = -2.125), suggesting that trust helps mitigate the challenges posed by the physical distance between the RA and CEO, enhancing rating accuracy. In other words, trust helps overcome information production difficulties associated with physical distance.

Flight Distance is the logarithm of 1 plus the shortest flight distance between the CEO and RA offices, calculated using global historical flight data. Similarly, column [2] examines the interaction term $Trust_{RA,CEO}$ × *Flight Distance* is also significantly negative (-0.004, t-statistic = -1.674), indicating that trust helps mitigate difficulties associated with flight distance, enhancing rating accuracy. *Flight Time* is the shortest flight time between the CEO and RA offices, estimated using global historical flight data. In Column [3], the interaction between $Trust_{RA,CEO}$ and *Flight Time* is significantly negative (-0.003, t-statistic = -1.748). These results collectively indicate that trust can alleviate the difficulties associated with distance and travel time, facilitating better information exchange and thus improving rating accuracy.

The negative interactions between trust and various distance measures in Table 5 support social capital theory, which posits that trust can facilitate the flow of information and resources (Coleman, 1988; Putnam, 1995; Nahapiet & Ghoshal, 1998). Specifically, trust enables analysts to capitalize on signals that may be difficult to verify, especially when physical barriers hinder direct communication. Trust becomes particularly valuable when face-to-face interactions are limited, as it can effectively bridge physical and communication gaps. By cultivating trust, analysts can rely more on the CEO's information, even when physical distance poses challenges. In essence, the trust serves as a proxy for physical proximity, ensuring that necessary information flows smoothly between the CEO and rating analyst, thereby facilitating accurate ratings despite geographical separation.

(2) External Information

Similar to the information production difficulty in the previous subsection, there are alternative ways to verify the signal quality instead of in-person communication. One of them is the information environment: if many other analysts or media verify one signal, there is less demand for verification and thus less role played by trust.

Table 9 investigates how the broader information environment influences the trust-rating accuracy relationship. Table 9 re-estimates the baseline OLS regression from Column [3] of Table 2, with cross-sectional tests across two measures of the information environment: *Low Analyst Coverage* and *Low Media Coverage*. *Low Media Coverage* assigns lower scores to bond issuers with a higher volume of media reports relevant to the firm. Similarly, *Low Analyst Coverage* assigns lower scores to issuers with greater analyst coverage. Column [1] shows the interaction term $Trust_{RA,CEO}$× *Low Media Coverage* being significantly negative (-0.367, t-statistic = -1.663). The results in Table 6 suggest that in environments with low media coverage, the reliance on trust might be increased, as external information sources provide sufficient information for rating accuracy. The interaction term $Trust_{RA,CEO}$× *Low Analyst Coverage* in column [2] is also significantly positive (-0.065, t-statistic = -2.052). This indicates that trust between the RA and CEO is more critical in firms with low analyst coverage, as external analysts' reports cannot provide additional layers of scrutiny and information, thus increasing the necessity of trust for accurate ratings.

The results in Table 9 show that the marginal value of trust declines when the external information environment is rich. Specifically, when widespread media coverage of the bond-issuing firm or multiple analysts focus on it, an abundance of external information sources becomes available to RAs, enabling them to cross-verify a substantial amount of data. As the transparency of external information increases, there is less noise in the overall information environment, reducing the cost of information verification for rating analysts. Rating analysts can easily compare the content of different sources of information and verify their truthfulness and accuracy, thus mitigating the over-reliance on a single source of information, such as CEO statements. An abundant external information environment serves as an alternative effect of trust. These results align with the view that trust is most beneficial in environments where external information is scarce, and reliance on internal sources of information is critical for accurate decision-making (Daft & Lengel, 1986). In contrast, the additional value of trust is less pronounced in information-rich environments. In summary, increased transparency of external information diminishes the importance of trust in promoting rating accuracy.

4.4.2 Spread & Covenant

Table 10 presents the OLS regression results examining the effect of trust from the rating analyst and the CEO on bond spread and covenants. The dependent variables are Bond Spread and Bond Covenants. Bond Spread is the difference between the bond offering yield and the U.S. treasury bond yield (bps). No. of Bond Covenants are defined as the count of the total number of covenants included in the bonds issued by the firm, covering payout-related covenants (DIV), investment-related covenants (INV), financing-related covenants (FIN), accounting-related covenants (ACC), and other types of covenants. The key independent variable, $Trust_{RA,CEO}$, is a standardized score reflecting the trust level from Moody's rating analyst to the issuer's CEO, the same as in the baseline regression table. $Trust_{CEO, RA}$ is the level of trust the CEO has in the RA. Columns [1] and [2] report the results with Bond Spread and Bond Covenants as the dependent variables, respectively. Columns [3] and [4] include an interaction term, $Trust_{RA,CEO}$ ×Bond Rating, to test the moderating effect of bond rating on the relationship between trust and the dependent variables. All models include a consistent set of control variables, as well as firm fixed effects, year fixed effects, and rating analyst fixed effects, ensuring that the results are robust and account for potential confounding factors.

The results in Column [1] show that $Trust_{RA,CEO}$ has a positive but insignificant effect on Bond Spread (3.897, t-statistic = 0.665), suggesting that the trust between RA and CEO does not significantly influence the bond spread. The lack of significance implies that while trust may play a role in reducing bond rating inaccuracy, it does not directly translate into lower bond spreads. The reasonable explanation is that market participants perceive the bond rating as a comprehensive measure of credit risk that already incorporates the trust factor; hence, the bond spread does not reflect additional trust levels. These results align with the concept of market efficiency (Fama, 1970), where all available information, including the perceived trustworthiness of management, is already reflected in security prices. In contrast, Column [2] shows a significant negative effect $Trust_{RA,CEO}$ on Bond Covenants (-0.008, t-statistic = -2.164), they indicate that higher trust levels associated with fewer covenants being included in bond agreements. This suggests that when there is high trust from the RA to the CEO, the perceived need for covenants decreases because trust acts as a substitute for formal contracting mechanisms.

Columns [3] and [4] introduce an interaction term, $Trust_{RA,CEO}$ ×Bond Rating, to test the moderating effect of bond rating on the relationship between trust and the dependent variables. $Trust_{RA,CEO}$ × Bond Rating is not significant for either Bond Spread (1.404, t-statistic = 1.208) or Bond Covenants (0.000, t-statistic = 0.036), suggesting that the moderating effect of bond rating on the relationship between trust and bond characteristics is minimal. This result rules out the possibility that the sensitivity of bond spread or covenant usage to rating changes depends on the level of trust between the RA and CEO.

Findings in Table 10 support the idea that trust and formal mechanisms such as covenants can act as substitutes. This result is consistent with the findings of Diamond (1984) on financial intermediation and delegated monitoring, where trust in management reduces the need for restrictive covenants as a monitoring tool. Trust can facilitate the flow of information and reduce the need for formal monitoring mechanisms (Coleman, 1988). When trust is high, it implies that the RA believes the CEO's disclosures are credible, reducing the perceived risk and, hence, the necessity for restrictive covenants. This is also consistent with the agency theory, which posits that covenants are included in debt contracts to mitigate agency costs (Jensen & Meckling, 1976). When trust mitigates these costs, the reliance on covenants decreases.

In summary, Table 10 highlights the nuanced role of trust in financial contracting. While trust can reduce the need for covenants, it does not significantly impact bond spreads, suggesting that markets efficiently price the effects of trust through bond ratings. This underscores the importance of understanding the interplay between informal trust and formal contracting mechanisms in corporate finance.

4.4.3 Moody & S&P

Table 11 examines whether trust can help Moody's ratings outperform those of its competitor, S&P. Instead of using Moody's performance relative to S&P as an alternative measure of rating accuracy, our focus here is on whether trust between rating analysts (RAs) and CEOs enhances Moody's ability to lead in the ratings market. We are particularly interested in understanding if trust can provide Moody's with an advantage over its peers.

The dependent variables in the table, $Leading_{dum}$ and $Leading_{count}$, Specifically, we first identify instances where Moody's and S&P assign different ratings to the same bond issued by the same firm. We then observe whether, within one year, S&P adjusts its rating in the direction of Moody's rating, thereby reducing the rating discrepancy. This scenario is defined as Moody's leading S&P. Due to the stringent criteria, the number of such observations in our sample is relatively limited.

The results in Column [1] and Column [3] that the coefficients of $Trust_{RA,CEO}$ and $Trust_{CEO,RA}$ are not statistically significant when considered without interaction. This indicates that unilateral trust—whether from the rating analyst to the CEO or from the CEO to the rating analyst—does not independently enable Moody's to lead S&P in the ratings industry. However, Columns [2] and [4], which include the interaction term $Trust_{RA,CEO} \times Trust_{CEO,RA}$ are significantly negative. The coefficient of the interaction term is -0.021 in Column [2] and -0.050 in Column [4], both statistically significant. These results suggest that mutual trust between RAs and CEOs significantly contributes to Moody's ratings leading those of S&P. This finding implies that trust enhances the timeliness and potentially the informativeness of Moody's ratings. In other words, the results in Columns [2] and [4] indicate that higher mutual trust increases the likelihood that Moody's rating will lead S&P's, and it also strengthens the extent to which Moody's ratings influence subsequent changes in S&P's ratings. This means that mutual trust can position Moody's ratings as more forward-looking and informative compared to its competitor.

Overall, the findings suggest that unilateral trust, whether from the RA to the CEO or vice versa, is insufficient to enable Moody's to outperform S&P. Only through the development of mutual trust can Moody's achieve industry leadership. This mutual trust likely facilitates more open and effective communication between RAs and CEOs, allowing analysts to gain a deeper understanding of the company's strategy and operations, and ultimately making more accurate and forward-looking rating judgments. Therefore, it can be concluded that it is not enough for either the RA to trust the CEO or the CEO to trust the RA independently. Only with mutual trust can Moody's truly secure its leading position in the ratings industry.

4.4.4 Alternative Variable

To further establish the robustness of our findings, we employed several alternative measures of rating inaccuracy, as summarized in Table 12. These measures provide different perspectives on the relationship between trust and rating accuracy, allowing us to confirm that our results are not driven by the specific definition of inaccuracy used in our baseline model. Column [1] uses $Inaccuracy_{9m}$, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within nine months. The negative and significant coefficient (-0.010, t-statistic = -1.694) indicates that higher trust is associated with lower rating inaccuracy even when the revision period is shortened to nine months. This suggests that trust leads to more accurate initial ratings, reducing the need for subsequent revisions within a shorter timeframe. In column [2], we use $Inaccuracy_{dum}$, a binary variable indicating whether Moody's initial bond rating has changed within one year. The negative and significant coefficient (-0.036, t-statistic = -2.845) indicates that higher trust reduces the likelihood of any rating change within a year. This further supports the robustness of our main finding that trust enhances rating stability and accuracy.

The robustness of our findings in Table 12 across these various inaccuracy measures underscores the importance of trust in improving rating accuracy. These results also align with theoretical expectations from information asymmetry and trust. Trust between the RA and CEO mitigates information asymmetry, leading to more accurate and timely bond ratings. This is consistent with the literature on trust and financial decision-making (Guiso et al., 2008), where trust reduces monitoring costs and the risk of opportunistic behavior, thereby improving the quality of financial decisions. Additionally, the significant result for the $Leading_{dum}$ suggests that trust improves the accuracy of Moody's ratings and enhances their relevance and informativeness compared to S&P's ratings. This supports the notion that trust can provide a competitive advantage in the credit rating industry by enabling more timely and accurate assessments (Manso, 2013). Those two measure further validating the effectiveness of trust in improving rating quality.

4.4.5 CFO & secondary RA

Table 13 presents the results in the relationship between the lead rating analyst, secondary rating analyst and the CEO (or CFO). Inaccuracy is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. The analysis includes two key independent variables. First, $Trust_{RA,CFO}$ measures the trust level between the CFO and Moody's lead rating analyst, excluding the CEO from the sample. Second, $Trust_{Secondary\ RA,\ CEO}$ is a standardized score indicating the trust level from Moody's secondary rating analyst to the issuer's CEO.

As can be seen from the regression results, neither RA's trust in CFO nor the second RA's trust in CEO has a significant impact on the accuracy of the rating report, indicating that only the trust between a specific RA and CEO can improve the accuracy of the rating report. Not all forms of trust have a significant impact on the accuracy of rating reports. In particular, the RA's trust in the CFO and the second RA's trust in the CEO did not significantly affect the accuracy of the rating report. This may be because the CFO and the CEO have different roles and responsibilities in the company, while the trust between the analyst and the CEO is more likely to be based on a deep understanding and consensus of the company's overall strategy, operations, and future development. This specific trust relationship helps analysts more accurately assess a company's credit profile, which improves the accuracy of rating reports.

To be clear, this result does not mean that CFOs are unimportant in the enterprise, or that their contributions are undervalued. As the core person of financial management of enterprises, CFO is responsible for ensuring the accuracy of financial reports, managing financial risks, and providing financial support for strategic decisions of enterprises. Their role is critical and directly related to the financial health and long-term stability of the business. However, the reason why analysts' trust in CEOs is more significant in improving the accuracy of ratings reports may be because trust plays a more critical role in the processing of soft information. Soft information usually involves the strategic direction of the enterprise, market potential, management capabilities and other factors that are difficult to quantify. In these aspects, as the top decision maker of the enterprise, CEO's leadership style, decision-making ability, industry insight and other characteristics have a profound impact on the development of the enterprise. Therefore, when analysts trust a CEO, they may be more willing to trust the CEO's statements about the company's strategy and future development, thus incorporating this information into the rating report and improving the accuracy of the rating. In contrast, the CFO's job is more focused on processing and analyzing hard data related to finance, which often has clear measures and verification methods, so the impact of trust is relatively small.

At the same time, this result also emphasizes the specificity and pertinence of trust relationship. In a complex business environment, trust is not a universally applicable resource, but needs to be built upon specific individuals, roles, and relationships. Only when a solid relationship of trust is established between the analyst and the CEO can this trust be translated into an effective force for improving the accuracy of rating reports. Therefore, rather than simply viewing trust as a universally valid factor, we need to focus on the specific context and conditions in which it arises and how it affects the accuracy and reliability of rating reports.

5. Conclusion

This study provides valuable insights into how trust between rating analysts (RAs) and CEOs influences credit rating accuracy. Our main finding is that higher levels of trust are significantly associated with greater rating accuracy. Trust facilitates more effective information exchange and reduces verification costs, with mutual trust between RAs and CEOs proving especially critical for improving outcomes. Mechanism tests demonstrate that RA trust in the CEO enhances rating accuracy when managerial information quality is high and analysts are experienced. Specifically, trust benefits experienced analysts who can leverage their expertise to interpret complex signals and make more precise judgments. However, the positive impact of trust depends on the quality of information provided by management. When managerial information quality is poor, trust may lead to over-reliance on misleading signals, which can increase rating inaccuracies.

We also find that RA who trust the CEO invest greater effort in preparing reports for that issuers. This extra effort leads to more thorough research and broader assessments, enabling analysts to evaluate the company from multiple perspectives and further enhance rating accuracy. Trust becomes especially important when physical distance barriers direct communication or when external information is limited, as it helps bridge gaps caused by information asymmetry. Conversely, in information-rich environments with ample media and analyst coverage, the marginal value of trust diminishes, as external information provides sufficient means for verification.

Despite its contributions, this study has limitations. The measurement of trust based on surname origins, may not fully capture the dynamic and nuanced nature of interpersonal trust. Future research could explore alternative trust measures, such as direct surveys or experimental methods, to validate and extend these findings. Additionally, potential unobserved variables might influence the trust-rating accuracy relationship. Future research could explore additional factors that may mediate or moderate this relationship. Furthermore, the study focuses on U.S. bond markets, and further research could examine whether these results hold in different institutional contexts and across various types of financial markets.

These findings carry significant implications for credit rating agencies (CRAs) and regulatory bodies. CRAs should carefully monitor the cultural trust between RAs and CEOs, as its effects can vary depending on the information environment. While trust can improve rating accuracy in high-quality information contexts, it may lead to biases or inaccuracies when information quality is low. CRAs must balance the benefits of culturally trusted RAs with the risks of over-reliance on trust in poor information environments. Regulators should establish mechanisms to prevent trust from causing complacency or bias in ratings, ensuring the integrity of credit ratings even in challenging information conditions.

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Table 1. Descriptive Statistics

This table provides summary statistics of variables used in the baseline model. Our sample includes 10,832 bond issuances by 916 firms in the U.S. primary bond market from 2000 to 2023. Variable definitions are provided in Appendix A.

	N	*Mean*	*Std. Dev.*	*Min*	*Median*	*Max*
	[1]	[2]	[3]	[4]	[5]	[6]
Inaccuracy	10,832	0.016	0.161	0	0	6
Trust $_{RA, CEO}$	10,832	0	1	-6.771	-0.055	2.606
Trust $_{CEO, RA}$	10,832	0	1	-8.319	-0.425	2.795
Bond Rating	10,832	16.65	4.823	2	18	21
Ln (1+No. of Issuance)	10,832	5.365	3.004	0	5.985	9.44
Ann. Type	10,832	0.858	0.349	0	1	1
R144A	10,832	0.084	0.278	0	0	1
Callable	10,832	0.987	0.112	0	1	1
Profitability	10,832	0.023	0.019	-0.221	0.017	0.127
MTB	10,832	1.45	0.852	0.533	1.093	13.478
Tangibility	10,832	0.163	0.244	0	0.010	0.962
Leverage	10,832	0.551	0.351	-0.680	0.578	2.259
Size	10,832	5.691	1.480	-0.507	6.728	6.728
Dif. Culture	10,832	0	1	-1.879	-0.300	3.396
Dif. Gender	10,832	0.475	0.499	0	0	1

Table 2. Trust and Bond Rating Inaccuracy

This table presents the OLS regression results examining the effect of trust between rating analysts and CEOs on bond rating inaccuracy. *Inaccuracy* is the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. $Trust_{RA, CEO}$ ($Trust_{CEO, RA}$) measures the level of trust from the rating analyst (CEO) toward the CEO (rating analyst). Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.:	*Inaccuracy*			
	[1]	[2]	[3]	[4]
$Trust_{RA, CEO}$		-0.029**	-0.014**	-0.005
		(-2.221)	(-2.102)	(-0.806)
$Trust_{CEO, RA}$	-0.031**		-0.021	-0.022
	(-1.999)		(-1.454)	(-1.602)
$Trust_{RA, CEO} \times Trust_{CEO, RA}$				-0.023**
				(-1.976)
Bond Rating	0.002	0.002	0.002	0.002
	(0.269)	(0.278)	(0.277)	(0.232)
Ln (1+No. of Issuance)	-0.015	-0.016	-0.015	-0.015
	(-1.346)	(-1.366)	(-1.355)	(-1.380)
Ann. Type	-0.019	-0.018	-0.019	-0.015
	(-0.683)	(-0.662)	(-0.674)	(-0.582)
R144A	-0.031***	-0.031***	-0.031***	-0.029***
	(-2.824)	(-2.795)	(-2.822)	(-2.679)
Callable	-0.032	-0.030	-0.031	-0.033
	(-0.820)	(-0.782)	(-0.805)	(-0.856)
Profitability	0.518**	0.511**	0.514**	0.527**
	(2.367)	(2.355)	(2.356)	(2.395)
MTB	0.016	0.018	0.017	0.018
	(1.270)	(1.374)	(1.318)	(1.386)
Tangibility	-0.102	-0.108	-0.108	-0.115
	(-0.825)	(-0.863)	(-0.864)	(-0.933)
Leverage	0.042	0.050	0.046	0.049
	(0.665)	(0.764)	(0.721)	(0.771)
Size	0.016	0.018	0.016	0.013
	(0.812)	(0.896)	(0.828)	(0.705)
Dif. Culture	-0.008	-0.006	-0.010	-0.008
	(-1.086)	(-0.970)	(-1.339)	(-1.189)
Dif. Gender	-0.018	-0.017	-0.018	-0.020
	(-1.297)	(-1.223)	(-1.291)	(-1.389)
Firm, Year, & RA FE	Yes	Yes	Yes	Yes
N	10,832	10,832	10,832	10,832
Adj. R^2	0.442	0.441	0.442	0.447

Table 3. Information Quality

This table presents OLS regression results on the impact of trust from the rating analyst toward the CEO on bond rating accuracy, focusing on the quality of managerial information. *Inaccuracy* is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. $Trust_{RA,CEO}$ quantifies the level of trust from the rating analyst to the CEO.

Table 3 re-estimates the baseline OLS regression model from Column [3] of Table 2. Columns [1] and [2] report the results of cross-sectional tests for two managerial information quality characteristics: *Accruals* and *Restatement*. *Accruals* are calculated using the Kothari Model, matching firms based on performance metrics such as Return on Assets (ROA). *Restatement* refers to the number of fraud restatements of the firm in the year before the rating release.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Inaccuracy*	
	[1]	[2]
$Trust_{RA,CEO}$	-0.013*	-0.015*
	(-1.781)	(-1.774)
Accruals	-0.012	
	(-0.157)	
$Trust_{RA,CEO}$ × *Accruals*	0.149*	
	(1.733)	
Restatement		0.047
		(1.054)
$Trust_{RA,CEO}$ × *Restatement*		0.056*
		(1.797)
Controls	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes
N	9,990	10,832
Adj. R^2	0.511	0.442

Table 4. Analyst Ability

This table provides OLS regression results assessing how rating analyst trust in the CEO influences bond rating accuracy, with particular emphasis on the analyst's information production capability. *Inaccuracy* is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. $Trust_{RA,CEO}$ quantifies the level of trust from the rating analyst to the CEO.

Table 4 re-estimates the baseline OLS regression model from Column [3] of Table 2. Columns [1] and [2] report the results of cross-sectional tests for rating analyst ability characteristics: *RA Seniority* and *RA Experience*, respectively. *RA Seniority* is a binary variable, set to 1 for senior roles (e.g., Senior Vice President, Managing Director) and 0 for junior to mid-level roles (e.g., Analyst, Senior Analyst, Senior Credit Officer). *RA Experience* is measured by the number of reports produced by Moody's rating analysts over the sample period from (2000-2023), scaled by 100.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Inaccuracy*	
	[1]	[2]
$Trust_{RA,CEO}$	-0.001	-0.001
	(-0.149)	(-0.190)
RA Seniority	-0.016	
	(-1.031)	
$Trust_{RA,CEO}$ × *RA Seniority*	-0.036**	
	(-2.359)	
RA Experience		-0.015
		(-1.062)
$Trust_{RA,CEO}$ × *RA Experience*		-0.009*
		(-1.862)
Controls	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes
N	10,832	10,832
Adj. R^2	0.445	0.445

Table 5. Rating Analyst Effort

This table presents OLS regression results examining the influence of rating analyst trust in the CEO on measures of analyst effort. The primary independent variable, $Trust_{RA,CEO}$, is quantifies the level of trust from the rating analyst to the CEO. Columns [1] and [2] analyze two metrics of rating analyst effort: *Word Count* and *Data Keywords*. *Word Count* is calculated as the logarithm of one plus the total word count of the full text in reports produced by the rating analyst. *Data Keywords* is calculated as the logarithm of one plus the count of specific terms related to data, metrics, indicators, instruments, and quantitative or qualitative descriptors.

All models include consistent control variables, along with fixed effects for bonds and years. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Word Count*	*Data Keywords*
	[1]	[2]
$Trust_{RA,CEO}$	0.068**	0.089**
	(2.374)	(1.995)
Controls	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes
N	9,266	9,266
Adj. R^2	0.880	0.639

Table 6. Omitted Variable

This table presents the robustness test results for the baseline OLS regression model from Column [3] of Table 2, analyzing the impact of rating analyst trust in the CEO on bond rating accuracy. *Inaccuracy* is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. $Trust_{RA,CEO}$ quantifies the level of trust from the rating analyst to the CEO.

Table 6 includes three columns, each incorporating a different robustness check. Column [1] includes six cultural distance dimensions: *Cultural Distance PDI*, *Cultural Distance IDV*, *Cultural Distance MAS*, and *Cultural Distance UAI*, *Cultural Distance LTO, Cultural Distance IVR,* based on Hofstede's cultural dimensions. Column [2] incorporates two dimensions of rating analyst characteristics: *RA Seniority* and *RA Experience*. Column [3] includes CEO fixed effects to control for CEO-specific heterogeneity.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.		*Inaccuracy*	
	[1]	[2]	[3]
$Trust_{RA,CEO}$	-0.017**	-0.015**	-0.014**
	(-2.253)	(-2.116)	(-2.003)
Cultural Distance PDI	-0.024		
	(-1.301)		
Cultural Distance IDV	0.005		
	(0.483)		
Cultural Distance MAS	0.011		
	(1.443)		
Cultural Distance UAI	-0.016*		
	(-1.811)		
Cultural Distance LTO	0.007		
	(0.944)		
Cultural Distance IVR	0.006		
	(0.778)		
RA Seniority		-0.010	
		(-1.311)	
RA Experience		-0.012	
		(-0.859)	
Controls	Yes	Yes	Yes
Firm & Year & RA, F.E.s	Yes	Yes	Yes
CEO F.E.s	No	No	Yes
N	10,832	10,826	10,832
Adj. R^2	0.445	0.443	0.437

Table 7. Reverse Causality

This table presents endogeneity test results to examine whether changes in CEOs lead to turnover among rating analysts (RA) at Moody's. The dependent variable, *RA Turnover*, in Columns [1] and [3], captures changes in the assigned rating analyst. The key independent variable, $Trust_{RA,CEO}$, in Columns [2] and [4], is a standardized measure of the trust level from Moody's rating analyst toward the CEO.

Columns [1] and [2] use a one-year lag (i.e., CEO death in year $t-1$ and RA turnover in year *t*), while Columns [3] and [4] use a two-year lag (i.e., CEO death in year $t-2$and RA turnover in year *t*). *CEO Exogenous* is a binary variable set to 1 if the CEO died while in office without the option to resign due to health reasons and 0 otherwise. This variable serves as an exogenous shock, testing the causal impact of CEO turnover on RA turnover.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	$RA\ Turnover$	$Trust_{RA,CEO}$	$RA\ Turnover$	$Trust_{RA,CEO}$
	[1]	[2]	[3]	[4]
$CEO\ Exogense$	-0.007	0.067	-0.000	-0.163
	(-0.955)	(0.533)	(-0.006)	(-1.503)
Controls	Yes	Yes	Yes	Yes
Bond, & Year, F.E.s	Yes	Yes	Yes	Yes
N	20,107	15,429	20,107	11,339
Adj. R^2	0.598	0.216	0.598	0.174

Table 8. Geographical Distance

This table presents the OLS regression results for cross-sectional variations in the effect of trust from the rating analyst to the CEO on bond rating accuracy, considering the distance between CEO and analysts. *Inaccuracy* is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. $Trust_{RA,CEO}$ quantifies the level of trust from the rating analyst to the CEO.

Table 8 re-estimates the baseline OLS regression from Column [3] of Table 2, with cross-sectional tests across three distance measures: *Geographical Distance*, *Flight Distance*, and *Flight Time*. *Geographical Distance* is the logarithm of one plus the distance (in km) between the CEO and rating analyst offices, calculated using the Haversine formula based on their latitude and longitude coordinates. *Flight Distance* represents the logarithm of one plus the shortest flight distance between these offices, derived from global historical flight data. *Flight Time* indicates the shortest flight time between the CEO and RA offices, also based on historical flight data.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.		*Inaccuracy*	
	[1]	[2]	[3]
$Trust_{RA,CEO}$	-0.007*	-0.007*	0.007
	(-1.907)	(-1.772)	(1.015)
Geographical Distance	-0.008		
	(-0.925)		
$Trust_{RA,CEO}$ × *Geographical Distance*	-0.006**		
	(-2.125)		
Flight Distance		-0.005	
		(-0.763)	
$Trust_{RA,CEO}$ × *Flight Distance*		-0.004*	
		(-1.674)	
Flight Time			-0.004
			(-1.237)
$Trust_{RA,CEO}$ × *Flight Time*			-0.003*
			(-1.748)
Controls	Yes	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes	Yes
N	4,212	4,212	4,212
Adj. R^2	0.0803	0.0801	0.0802

Table 9. External Information

This table presents the OLS regression results for cross-sectional variations in the effect of trust from the rating analyst to the CEO on bond rating accuracy, specifically focusing on the information environment of the bond issuer. *Inaccuracy* is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. $Trust_{RA,CEO}$ quantifies the level of trust from the rating analyst to the CEO.

Table 9 re-estimates the baseline OLS regression from Column [3] of Table 2, with cross-sectional tests across two measures of the information environment: *Low Analyst Coverage* and *Low Media Coverage*. *Low Media Coverage* assigns lower scores to bond issuers with a higher volume of media reports relevant to the firm. Similarly, *Low Analyst Coverage* assigns lower scores to issuers with greater analyst coverage.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Inaccuracy*	
	[1]	[2]
$Trust_{RA,CEO}$	-0.114*	-0.110**
	(-1.758)	(-2.575)
Low Media Coverage	0.011	
	(1.247)	
$Trust_{RA,CEO}$ × *Low Media Coverage*	-0.367*	
	(-1.663)	
Low Analyst Coverage		0.008
		(0.196)
$Trust_{RA,CEO}$ × *Low Analyst Coverage*		-0.065**
		(-2.052)
Controls	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes
N	10,175	10,302
Adj. R^2	0.496	0.428

Table 10. Spread, Covenant, and Trust

This table presents OLS regression results analyzing the effect of rating analyst trust in the CEO on bond spread and covenants. The dependent variables are *Bond Spread*, defined as the difference (in basis points) between the bond offering yield and the U.S. Treasury bond yield, and *Bond Covenants*, defined as the total count of covenants included in bonds issued by the firm. Bond covenants cover several categories: payout-related covenants (DIV), investment-related covenants (INV), financing-related covenants (FIN), accounting-related covenants (ACC), and other types.

$Trust_{RA,CEO}$ quantifies the level of trust from the rating analyst to the CEO. Columns [1] and [2] report results with *Bond Spread* and *Bond Covenants* as the dependent variables, respectively. Columns [3] and [4] include an interaction term, *Trust* × *Bond Rating*, to examine the moderating effect of bond rating on the relationship between trust and the dependent variables.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Spread*	*No. of Covenants*	*Spread*	*No. of Covenants*
	[1]	[2]	[3]	[4]
$Trust_{RA,CEO}$	3.897	-0.008**	-14.994	-0.008
	(0.665)	(-2.164)	(-0.871)	(-0.914)
$Trust_{CEO,RA}$	-3.669	-0.001	-2.691	-0.001
	(-0.602)	(-0.335)	(-0.440)	(-0.335)
Bond Rating	-31.372***	-0.005***	-31.049***	-0.005***
	(-8.453)	(-2.776)	(-8.426)	(-2.770)
$Trust_{RA,CEO}$ × *Bond Rating*			1.404	0.000
			(1.208)	(0.036)
Controls	Yes	Yes	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes	Yes	Yes
N	3,177	10,832	3,177	10,832
Adj. R^2	0.748	0.841	0.748	0.841

Table 11. Moody vs. S&P

This table presents whether trust enables Moody's rating analysts to lead their rivals (S&P rating analysts). The dependent variable in columns [1] and [2], $Leading_{dum}$, measured as a binary variable indicating whether Moody's initial bond rating leads to S&P's bond rating within one year. $Leading_{cont}$ in columns [3] and [4] measured as the extent to which Moody's initial bond rating leads S&P's bond rating within one year.

$Trust_{RA,CEO}$ is a standardized score reflecting the trust level from Moody's rating analyst to the issuer's CEO. All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	$Leading_{dum}$ [1]	$Leading_{dum}$ [2]	$Leading_{cont}$ [3]	$Leading_{cont}$ [4]
$Trust_{RA,CEO}$	0.012	0.026	0.021	0.053
	(0.425)	(0.791)	(0.545)	(1.324)
$Trust_{CEO,RA}$	-0.002	-0.006	0.025	0.014
	(-0.070)	(-0.233)	(0.638)	(0.385)
$Trust_{RA,CEO} \times Trust_{CEO,RA}$		-0.021**		-0.050***
		(-1.983)		(-3.500)
Controls	Yes	Yes	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes	Yes	Yes
N	2,193	2,193	2,193	2,193
Adj. R^2	0.623	0.624	0.634	0.639

Table 12. Alternative Measures of Inaccuracy

This table presents robustness test results using alternative measures of inaccuracy in bond ratings. *Inaccuracy* is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year. The table examines five alternative inaccuracy measures, including $Inaccuracy_{9m}$ measured as the absolute difference (in notches) between Moody's initial bond rating and its nine-month revision, and $Inaccuracy_{dum}$ measured as a binary variable indicating whether Moody's initial bond rating has changed within one year.

$Trust_{RA,CEO}$ is a standardized score reflecting the trust level from Moody's rating analyst to the issuer's CEO. All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	$Inaccuracy_{9m}$ [1]	$Inaccuracy_{dum}$ [2]
$Trust_{RA,CEO}$	-0.010* (-1.694)	-0.036*** (-2.845)
Controls	Yes	Yes
Firm, Year & RA, F.E.s	Yes	Yes
N	10,832	10,832
Adj. R^2	0.673	0.240

Table 13. CFO and Secondary Rating Analyst

This table presents the results in the relationship between the lead rating analyst, secondary rating analyst and the CEO (or CFO). *Inaccuracy* is defined as the absolute difference (in notches) between Moody's initial bond rating and its revised rating within one year.

The analysis includes two key independent variables. First, $Trust_{RA,CFO}$ measures the trust level between the CFO and Moody's lead rating analyst, excluding the CEO from the sample. Second, $Trust_{Secondary\ RA,\ CEO}$ is a standardized score indicating the trust level from Moody's secondary rating analyst to the issuer's CEO.

All models include firm, year, and rating analyst fixed effects, as well as a consistent set of control variables. Variable definitions are provided in Appendix A. The t-statistics reported in parentheses are based on standard errors clustered by firm. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Inaccuracy*	
	[1]	[2]
$Trust_{RA,CFO}$	-0.000	
	(-0.017)	
$Trust_{Sec.\ RA,\ CEO}$		-0.007
		(-0.685)
Controls	Yes	Yes
Firm, Year, & RA, F.E.s	Yes	Yes
N	6,424	6,570
Adj. R^2	0.597	0.445

Appendix A. Variable Definitions

This table provides detailed definitions of the variables we use in our analysis and information on the source of each data item.

Variable name	Definition	Data source
Inaccuracy	Measured as the absolute difference (in notches) between Moody's initial bond rating and the revision rating within one year. $Inaccuracy\_level_{j,t} = \frac{1}{N-1}\sum_{k=1}^{N-1}\left\|R_{j,t_k} - R_{j,t_0}\right\|$	Mergent FISD
$\text{Trust}_{\text{RA,CEO}}$	A standardized score indicating the trust level from Moody's rating analyst to the issuer's CEO, calculated based on the three most frequent origin countries associated with their surnames and the trust levels between these countries. $Trust_{i\to j} = \sum_{C1=1}^{3}\sum_{C2=1}^{3} P_{i,C1}\, P_{j,C2} Trust_{C1\to C2}$	Eurobarometer; Ancestry
$\text{Trust}_{\text{CEO,RA}}$	A standardized score reflecting the level of trust from the issuer's CEO toward Moody's rating analyst, calculated similarly to $\text{Trust}_{RA,CEO}$ by considering the three most common origin countries associated with their surnames and the respective inter-country trust levels.	Eurobarometer; Ancestry
Bond Rating	Moody's bond rating on a scale (AAA=21, AA+=20, ..., CCC-=3, CC=2, DDD and lower =1).	Mergent FISD
Ln(1+No. of Issuance)	Logarithm of 1 plus firm's issuance experience in the primary market over the sample period (2000-2023).	Mergent FISD
Ann. Type	1 for rating action announcements and 0 for other types of announcements.	Moody's official website
R144A	The dummy variable is equal to 1 if the bonds are type R144A, 0 otherwise.	Mergent FISD
Callable	The dummy variable is equal to 1 if the bonds are callable, 0 otherwise.	Mergent FISD
Profitability	The book value of assets scales operating income before depreciation.	Compustat
Size	Natural logarithm of net sales adjusted for inflation to the year 2000 (in 2000 $ U.S.).	Compustat
Leverage	Net book leverage, is calculated as the sum of long-term debt and short-term debt minus cash and cash equivalents, divided by the book value of assets.	Compustat
MTB	Market value of total assets scaled by the book value of assets.	Compustat

Tangibility	Net property, plant, and equipment scaled by book value of assets.	Compustat
Dif. Cultural	Average cultural distance score between RA and CEO. Calculated as $Culture\ Distance_{i,j} = \sqrt{\sum_{k=1}^{4} \left(I_{k,i} - I_{k,j}\right)^2 / V_k}$, using Hofstede's cultural six dimensions (IDV, UAI, PDI, MAS, LTO, IVR).	Hofstede (2001, 2010); *Ancestry*
Dif. Gender	The dummy variable is equal to 1 if the CEO and the RA are of different genders, and 0 if they are of the same gender.	Moody's official website; BoardEX; Genderize.io
Word Count	Calculated as the logarithm of 1 plus the total word count of the complete text in reports produced by the rating analyst.	Moody's official website
Data Keywords	Calculated as the logarithm of 1 plus the count of specific terms related to data, metrics, indicators, instruments, and quantitative or qualitative descriptors within the rating analyst's report.	Moody's official website
Low Media Coverage	A variable that assigns lower scores to bond issuers with a higher volume of media reports relevant to the firm.	RavenPack
Low Analyst Coverage	A variable that assigns lower scores to bond issuers with greater levels of analyst coverage.	I/B/E/S
RA Seniority	A dummy variable indicating the seniority of Moody's rating analysts. It equals 1 for senior positions (corresponding to Senior Vice President and Managing Director) and equals 0 for junior to mid-level positions (corresponding to Analyst, Senior Analyst, and Senior Credit Officer).	Moody's official website
RA Experience	Number of reports written by the Moody's rating analyst during the sample period from 2000 to 2023, divided by 100.	Moody's official website
Geographical Distance	The logarithm of 1 plus the distance (in km) between the CEO and RA offices, calculated using the Haversine formula based on their latitude and longitude coordinates.	BoardEX; Moody's official website; Google API
Flight Distance	The logarithm of 1 plus the shortest flight distance between the CEO and RA offices, calculated using global historical flight data.	BoardEX; Moody's official website; OpenSky Network
Flight Time	The shortest flight time between the CEO and RA offices, estimated using global historical flight data.	BoardEX; Moody's official website; OpenSky Network
Accruals	Discretionary accruals calculated using the Kothari Model, matching firms based on performance metrics such as Return on Assets (ROA).	Compustat
Restatement	Number of total restatements of the firm in	

	the year before the rating release, including both material and fraud restatements.	
Cultural Distance UAI	The difference in Uncertainty Avoidance Index (UAI) scores between the RA and the CEO, based on Hofstede's cultural dimensions.	Hofstede (2001)
Cultural Distance PDI	The difference in Uncertainty Avoidance Index (UAI) scores between the RA and the CEO, based on Hofstede's cultural dimensions.	Hofstede (2001)
Cultural Distance MAS	The difference in Masculinity (MAS) scores between the RA and the CEO, based on Hofstede's cultural dimensions.	Hofstede (2001)
Cultural Distance IDV	The difference in Individualism (IDV) scores between the RA and the CEO, based on Hofstede's cultural dimensions.	Hofstede (2001)
Cultural Distance LTO	The difference in Long-Term Orientation (LTO) scores between the rating analyst (RA) and the CEO, based on Hofstede's cultural dimensions.	Hofstede (2010)
Cultural Distance IVR	The difference in Indulgence versus Restraint (IVR) scores between the rating analyst (RA) and the CEO, based on Hofstede's cultural dimensions.	Hofstede (2010)
CEO Exogenous	A dummy variable set to 1 if the CEO died while in office without the option to resign due to health reasons and 0 otherwise.	BoardEX; CEO Dismissal Database (Gentry et al, 2021)
Bond Spread	Difference between bond offering yield and the U.S. treasury bond yield (bps).	Mergent FISD
Bond Covenants	Count of the total number of covenants included in the bonds issued by the firm, covering payout-related covenants (DIV), investment-related covenants (INV), financing-related covenants (FIN), accounting-related covenants (ACC), and other types of covenants.	Mergent FISD

Appendix B. Sample Filter

This table represents the data processing during the research and the number of corporate bonds remaining after each step of merging and filtering.

	No. of Firm	*No. of Bond*
Initial sample: all bond issuance in FISD between Q1 2000 and Q3 2023	8,422	262,750
Only keep *Moody's* bond rating	-1,224	-76,695
Exclude bonds with missing firm information in Compustat	-4,296	-3,267
Merge *Moody's* rating announcement	-489	-3,913
Exclude bonds with missing CEO information in *BoardEX*	-596	-34,984
Exclude observations with missing trust scores in *Eurobarometer* or culture origin data in *Ancestry.com*	-145	-4,651
Exclusion of industry-specific reports	-50	-12,621
Exclude floating rates bonds and bonds with optional features (e.g., convertible bonds, put-able bonds, exchangeable bonds, bonds with a sinking fund)	-115	-5,361
Exclude bonds with missing firm and bond controls	-78	-3,421
Exclude bonds with missing cultural and gender controls	-493	-9,064
Final Sample	**916**	**10,832**