Can Trust Enhance Credit Rating Accuracy?

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Abstract

This study investigates the role of trust on credit rating accuracy. Utilizing data from 10,955 issuances by 929 firms in the U.S. primary bond market from 2000 to 2023, we show robust evidence that a higher trust from the rating analyst to the CEO is associated with a more accurate rating, suggesting that trust allows rating analysts to extract valuable content from noisy information released by the CEO. Furthermore, we find that rating analysts' trust in the CEO enhances rating accuracy when managerial information quality is high, analysts are experienced, and external information is limited. In addition, we show that trust becomes particularly valuable when analysts and CEOs are geographically distant, mitigating communication barriers.

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). Nevertheless, trust is not all harmless. Trust can also trigger the spread of misleading information and overreliance on low-quality information 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 analysts (RAs) in the CEO enhances or worsens rating accuracy?

We establish our hypothesis based on the information flow from the CEO to the rating analysts. Signaling theory suggests that CEOs are incentivized to release information to investors and rating analysts to transmit the firm's quality to obtain better ratings and reduce the cost of financing (Spence, 1973). In this study, we classify the information into two categories: clear information, which is easy to verify, such as audited financial statements, and noisy information, which is more ambiguous and requires further validation. Certain informal characteristics among analysts, such as gender or cultural similarities, may help to verify ambiguous information (Guiso et al., 2009). However, some noise signals still remain, which are hard to verify. Analysts with higher trust in the CEO may rely on this information without further verification. However, whether trusting this noisy information could enhance or worsen the rating accuracy is an empirical question. To test whether trust-based behavior improves the accuracy of credit ratings, we propose two competing hypotheses. On the one hand, the higher the RA's trust in the CEO, the more accurate the rating will be, assuming that most trusted information is valuable and reduces information asymmetry (Coleman, 1988). In contrast, if trusted information is largely noisy and potentially misleading to RAs, higher levels of RA trust in CEOs may associated with lower rating accuracy (Graham, Harvey, & Rajgopal, 2005).

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 10,955 issuances across 929 U.S. firms. We calculate the rating inaccuracy based on subsequent rating revisions within one year of the

[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.

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 from RA to 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 includes ordinary least squares (OLS) regression models with fixed effects to control for firm, year, and analyst-specific factors. The regression models account for bond-level, firm-level, and pair-level control variables to isolate the effect of trust on rating accuracy. The empirical results consistently show a negative relationship between trust from RAs to CEOs and credit rating inaccuracy, emphasizing that higher trust levels generally reduce rating inaccuracy. Our results support our hypothesis that when RAs have a high level of trust in the CEO, they are more likely to accept potentially useful content within noisy information, interpreting it with a more open and inclusive attitude. Trust enables RAs to identify and utilize valuable signals that others may miss due to verification difficulties, improving credit rating accuracy. The results are not only statistically significant but also economically significant. Specifically, a one-standard-deviation increase in trust reduces average rating inaccuracy by 0.1875 standard deviations.[2]

In addition, we document that RA's trust in the CEO improves rating accuracy under specific conditions. Our cross-sectional analysis shows that trust enhances rating accuracy when 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. Furthermore, trust is more effective when external information sources, such as media and analyst coverage, are limited. Trust is particularly valuable when analysts and CEOs are geographically distant, bridging communication gaps. 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

[2] This result is calculated by dividing the coefficient of -0.030 (from model [4] in Table 2, which is the baseline results) by the standard deviation of inaccuracy (0.16), resulting in a value of -0.1875.

that trust acts as a substitute for formal contracting mechanisms, reducing the need for restrictive covenants when trust levels are high.

Robustness tests confirm these findings. We employ alternative measures of trust and inaccuracy to ensure the robustness of our results. For alternative trust measures, we include different combinations of RA and CEO trust levels and variations involving secondary RA and CFO.[3] For inaccuracy measures, we test definitions including rating changes within six months and two years, in addition to our baseline measure of one-year rating changes. We also use a dummy variable indicating whether the rating has changed within one year. Our analysis includes robustness tests with supplementary control variables, various clustering methods, and alternative fixed effects specifications. These tests address potential omitted variable concerns and ensure that specific model choices or data peculiarities do not drive our findings. By incorporating these additional layers of analysis, we confirm the stability and reliability of our findings, demonstrating the robustness of the trust-rating accuracy relationship across different contexts and conditions.

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)

[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.

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 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

In previous sections, we explored the importance and factors influencing credit ratings (Section 2.1) and the multiple roles of trust in financial relationships (Section 2.2), respectively. This section will further develop the discussion by focusing on whether ratings analysts' trust in the CEO plays a crucial role in rating accuracy.

As a company representative, the CEO has incentives to signal to market participants through information releases to obtain better credit ratings and, thus, lower financing costs. The signaling theory suggests that to reduce information asymmetry, managers tend to send signals about their firms' quality to outsiders (Spencer, 1973). For example, the CEO transmits information to RA through various forms (e.g., financial statements, regulatory filings, public announcements, Management Discussion and Analysis (MD&A), conference calls, private communications, social media, etc.). In this study, we classify the information released by CEOs into two categories: clear information that all RAs can use without extensive validation and hard-to-verify noisy information that needs further validation. Figure 1 illustrates the information flow process from the CEO to the RA, highlighting the distinction between clear and noisy information. The first type usually consists of audited financial statements, which are transparent, objective, and easily verifiable. RAs can use this to determine the firm's quality based on its fundamental characteristics. The noisy information is more complex and ambiguous for RAs that need further verification because it can be interpreted in multiple ways and lacks clear implications.

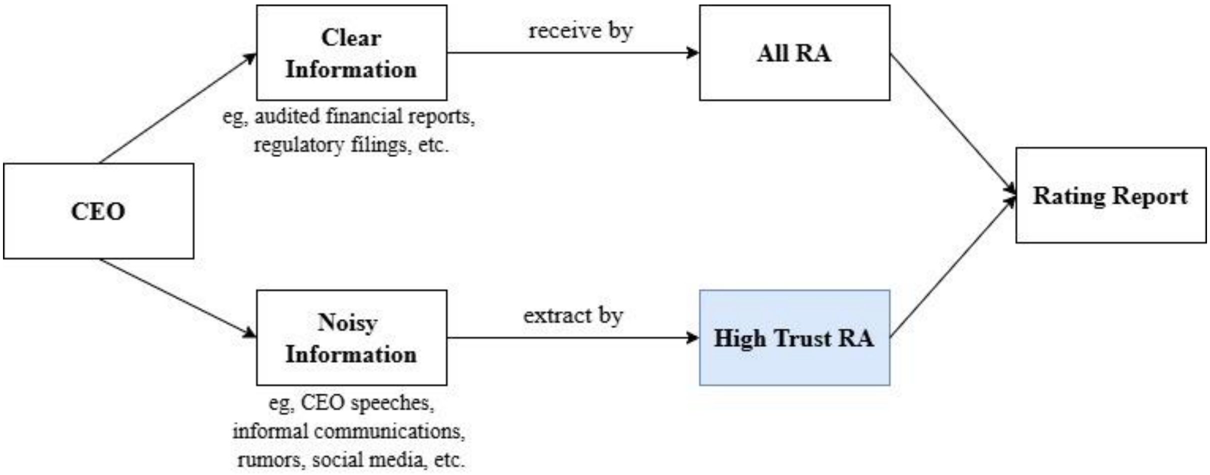

Figure 1. Information Flow from CEO to RA

The second category of information often contains a lot of noise, while certain informal characteristics such as gender or cultural similarities between the CEO and analyst can help verify this information (Guiso et al., 2009). Similar characteristics can reduce misunderstandings in communication and enhance the credibility and transparency of information. However, some noisy signals cannot be identified through the similarities of these informal characteristics. In such cases, RAs with higher trust in the CEO may extract and utilize this information, even without extensive verification. For example, a French RA tends to trust a Swedish CEO more than an Italian CEO. In that case, he/she may be more likely to capture and rely on the information conveyed by the Swedish CEO than the information conveyed by the Italian CEO. That raises the empirical question: does this trust-based behavior improve/worsen credit rating accuracy?

When writing rating reports, RA uses financial reports (e.g., 10K/10Q) and regulatory disclosures (e.g., SEC legal filings) as core information sources. In addition to these standard pieces of information, RA pays close attention to ambiguous information such as the CEO's public speeches, attitudes on social media, or private communications. For example, a CEO's public speeches provide more direct and timely information but can also contain subjective overtones. Trust enhances the trustworthiness of these signals, making it easier for RA to view the information provided by the CEO as a true reflection of firm quality (Connelly et al., 2011). When RAs choose to believe the CEO and utilize this information, this reduces verification costs, facilitates the flow of information, and improves cooperation efficiency, which may increase the rating accuracy. Based on the theoretical framework and fundamentals described above, we propose our first hypothesis:

Hypothesis 1a (H_{1a}): A higher level of trust from RAs to CEOs is associated with more accurate credit ratings, ceteris paribus.

This hypothesis assumes that most of the information received by RAs is valuable.RAs' high level of trust in the CEO helps them to distinguish between useful information and noise effectively, thereby reducing information asymmetry between the two parties (Coleman, 1988). This argument aligns with previous research, which shows that trust significantly affects information production and transmission quality in the financial market (Kempf, 2020; Cornaggia et al., 2017; Fracassi et al., 2016).

However, if the information from the CEO, which RA trusts, is mainly noisy, it can related to misleading and distorted information (Healy & Palepu, 2001; Graham et al., 2005). When CEO release low-quality managerial information, RA trust may lead them to over-rely on this data, be misled by manipulated information, and ignore potential warnings or alternative sources of validation (Dechow, Sloan, & Sweeney, 1995). For example, rumors and gossip are also common in the financial market. Private communications and rumors may provide potentially valuable information and contain misleading content. Therefore, we propose the alternative hypotheses:

Hypothesis 1b (H_{1b}): A higher level of trust from RAs to CEOs is associated with less accurate credit ratings, ceteris paribus.

In summary, if the empirical results support **H1a**, it indicates that the information provided by CEOs trusted by RAs is valid on average; if the empirical results support **H1b**, it implies that the information RAs choose to trust has less valuable content. This hypothesis emphasizes the importance of considering the information quality provided by CEOs when assessing the impact of trust on rating accuracy.

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

The sample period for this study covers bond-issue-level observations from the first quarter of 2000 to the second quarter of 2023. Our baseline panel includes 10,955 issuances by 929 firms in the U.S. primary bond market. The primary sources of data are as follows:

First, bond issue and rating data are obtained from the Mergent Fixed Income Securities Database (FISD), which provides detailed information on bond issuances, including ratings, yields, and other relevant bond-level metrics. Second, trust scores are derived from the Eurobarometer survey data. The Eurobarometer has conducted public opinion surveys in European Union (E.U.) member nations since 1970, with coverage expanding from five countries in 1970 to 16 countries by 1996. Third, RA information is collected manually from Moody's official website; CEO names and locations are sourced from the BoardEX Database. RA surnames are matched to their origin countries using *Ancestry.com*, and CEO names are processed similarly. This approach follows the methodologies used by Bae et al. (2023), Hagendorff et al. (2023), and Bhagwat & Liu (2020), who linked trust measures to individuals' countries of origin based on surnames.

Additional financial data is extracted from the Compustat database for firm-level financial metrics. Cultural data is sourced from Hofstede's cultural dimensions, and additional hand-collected data is collected from *Ancestry.com*. Gender data is retrieved from *Genderize.io* to identify the gender of RAs and CEOs. For cross-sectional tests, additional data include media coverage 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.

3.2 Sample Selection

Following Kisgen et al.'s (2020) methodology, we collected rating announcement information from Moody's official website. Moody's issues four types of announcements: Announcement, Rating Action, Assessment Announcement (since 2021), and Announcement of Periodic Review. Our study focuses exclusively on U.S. companies and includes only the "Announcement" and "Rating Action" types due to data availability constraints before 2021. We retained market segments such as corporates, financial institutions, and insurance; while excluding segments like infrastructure, funds, sovereigns, structured finance, and public finance, as these are outside the scope of our research, as these segments have distinct characteristics and are beyond the scope of our study.

To ensure the robustness of our analysis, we excluded any bond issues associated with more than three entities unless they were related, such as parent and subsidiary companies. This follows the methodology of Kisgen et al. (2020), which deemed reports as firm-specific if linked to fewer than four entities.

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 majority of offices are in New York City (NYC), which accounts for over 90% of the total, followed by Frankfurt and Toronto, with some based in London, Hong Kong, Sydney, and Tokyo.

Additionally, 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. Bonds with embedded options or unique features, such as asset-backed, puttable, exchangeable, convertible, private placement, and sinking fund bonds, were excluded to maintain consistency. Callable bonds are retained, but we created a callable dummy variable and controlled for it in our regressions.

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).[4]

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[4] 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

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).[5] 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:

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

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 $Trust_{C1\rightarrow C2}$ 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.

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.[6] For example, in our database, 54.09% of the subjects with the

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).

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

[6] 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

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 robustness checks include secondary RA and Chief Financial Officers (CFOs).

3.4 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 include all subsequent upgrades or downgrades to t + h within one year. *N−1* ensures 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 *t*, and R_{j,t_k} represents the k^{th} updated rating for bond *j* within the period extending to *t* + *h*, *h* will equal one calendar year. Bonds that experience a change in either CEO or RA between time *t* and *t+h*

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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.

are excluded from the sample to ensure consistency. This measure of inaccuracy captures the deviations in ratings over time, providing a robust proxy for assessing the accuracy of initial ratings assigned by analysts.

Moreover, the attractive institutional feature of Moody's organization, where a separate internal surveillance team performs subsequent rating adjustments, ensures these adjustments are not under the direct influence of the analyst who assigned the initial rating (Kempf, 2020). Moody's rating process begins with pre-engagement, where an introductory meeting or teleconference is held to discuss the rating process. This is followed by the assignment of an analytical team, typically led by a "Lead Analyst," who begins the credit analysis by collecting relevant information. The issuer is asked to provide both financial and non-financial information, which the Lead Analyst then analyzes. Analysts discuss their ratings, including credit strengths and weaknesses, with issuers before formulating a recommendation for consideration by a rating committee. The rating committee's decision is then communicated to the issuer, and the rating is disseminated to the public. The final step involves surveillance, where credit ratings are monitored and adjusted as necessary by a separate team, ensuring the accuracy and objectivity of the ratings; all monitored credit ratings are reviewed at least once every twelve months (Moody's Investors Service). This separation adds credibility to using subsequent rating corrections to measure inaccuracy.

3.5 Empirical Methodology Model

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:

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

where *j* refers to bonds and *i* refers to issuers. The key independent variable $Trust_{RA,CEO}$ is the trust score from the rating analyst to the CEO, as discussed in section 3.3, and the dependent variable $Inaccuracy_{j,t}$ is the rating inaccuracy, as defined in section 3.4.

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); 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 *Gender Difference* and *Cultural Distance*. *Gender difference* 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. Following Bae et al. (2023), *Cultural Distance* is calculated as the average cultural distance between the RA and CEO, using Hofstede's (1984) cultural dimensions (IDV, UAI, PDI, MAS):

$$Culture\ Distance_{i,j} = \sqrt{\sum_{k=1}^{4} \left(I_{k,i} - I_{k,j}\right)^2 / V_k}$$

where $\boldsymbol{I_{k,i}}$ and $\boldsymbol{I_{k,j}}$ represent RA *i*'s and CEO *j*'s average weighted cultural scores on cultural dimension *k*, and $\boldsymbol{V_k}$ is the in-sample variance of $I_{k,i} - I_{k,j}$.[7]

These control variables help account for various factors that might influence rating accuracy, ensuring that the impact of trust is isolated and accurately measured. We also include the three different fixed effects, $\gamma_{Year}, \delta_{Firm}, \phi_{RA}$ represent the year, firm, and rating analyst fixed effects.

[7] 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).

4. Empirical Results

4.1 Trust and Rating Accuracy

Table 1 provides summary statistics for the bond-issue-level observations in our sample, which includes 10,955 issuances by 929 firms in the U.S. primary bond market from 2000 to 2023. As we discussed in section 3, 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 0.160, indicating that most bond ratings have low inaccuracy within our sample. $Trust_{RA,CEO}$ variable is standardized with a mean of 0 and a standard deviation of 1, reflecting a range from -2.511 to 1.974.

Bond-level characteristics include the average bond rating of 16.605, 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(No. of Issuance)* show means 5.330, highlighting the distribution of the firm's issuance experience. Within our sample, approximately 8.6% of the bonds are classified under Rule 144A, which means these bonds can be traded among Qualified Institutional Buyers (QIBs) without SEC registration. While Callable bonds represent 98.7% of the 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 1.444, indicating that, on average, the market values these firms slightly higher than their book value, reflecting a positive but not overly optimistic market perception. *Tangibility* shows a mean of 0.164, *Leverage* has an average of 0.548, and the natural logarithm of net sales (*Size*) averages 5.678, implying that the firms in our sample have a relatively small portion of their assets in tangible form, with moderate levels of debt, and are generally fairly large, which may include many large and established firms.

Pair-level characteristics are represented as *Cultural Distance* and *Difference Gender*. The variable *Difference Gender* indicates that approximately 47.1% of the CEO-RA pairs in our sample are of different genders. This diversity in gender pairings is significant as it may influence the dynamics of trust and communication between the CEO and the rating analyst. The variable *Cultural Distance*, which measures the average cultural distance score between the RA and CEO using Hofstede's cultural dimensions, has a mean of 1.586. This suggests considerable cultural diversity within the CEO-RA pairs, which can impact the effectiveness of their interactions and the overall rating accuracy.

To examine the effect of trust on rating accuracy, we estimate baseline OLS regression models in Table 2. The results in Table 2 show a consistent and significant negative relationship between $Trust_{RA,CEO}$ and *Inaccuracy* across all models. This suggests that higher trust from the rating analyst to the CEO is associated with lower rating inaccuracy (higher rating accuracy). In model [1], the coefficient for $Trust_{RA,CEO}$ is -0.025, significant at the 1% level (t-statistic = -6.445), indicating that higher trust levels are associated with lower rating inaccuracies. This relationship remains robust even after including various control variables in models [2] through [4]. In all specifications from Column [1] to Column [4], we include 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 0.437 to 0.442, indicating a reasonable fit of the models to the data (Roberts & Whited, 2013).

The economic significance behind the observed effect can be quantified by examining the standard deviation of inaccuracy. The coefficient of -0.030 (model [4]) divided by the standard deviation of inaccuracy (0.16) results in a value of -0.1875. This result indicates that for each one-unit increase in $Trust_{RA,CEO}$, the Rating *Inaccuracy* decreases by 0.1875 standard deviations on average. This finding underscores the substantial impact that trust between RAs and CEOs can have on the accuracy of credit ratings, demonstrating that higher levels of trust can significantly reduce rating inaccuracies.

In Column [1], the regression does not include any control variables, allowing us to observe the raw effect of $Trust_{RA,CEO}$ on rating inaccuracy. The coefficient for $Trust_{RA,CEO}$ is -0.025 and is highly significant (t-statistic = -6.445), indicating that higher trust levels are associated with lower rating inaccuracies. In column [2], we add bond-level controls, such as *Bond Rating*, *Ln(No. of Issuance)*, *R144A*, and *Callable*. Including these controls helps account for the bonds' characteristics, which could impact rating accuracy. For instance, the negative and significant coefficient of *Ln(No. of Issuance)* suggests that firms with more issuance experience tend to have lower rating inaccuracies. Also, the negative coefficient of *R144A* suggests that bonds issued under Rule 144A might be associated with higher rating accuracy.[8] This could be because qualified institutional buyers (QIBs), who are sophisticated investors, demand higher transparency and due diligence from issuers, thereby reducing information asymmetry and leading to more accurate initial ratings by analysts. This aligns with the findings of Bushee and Goodman (2007) and Chen, Goldstein & Jiang (2015), who highlight the role of institutional investors in enhancing corporate transparency and governance standards. The *Bond Rating* variable is insignificant in any models, suggesting that the rating level does not significantly affect rating inaccuracy. Despite these additions, the coefficient for $Trust_{RA,CEO}$ remains significant and unchanged (-0.025, t-statistic = -6.387), demonstrating the robustness of the relationship.

In column [3], firm-level controls are added, including *Profitability*, *MTB*, *Tangibility*, *Leverage*, and *Size*, to capture the financial and operational characteristics of the issuing firms. One plausible explanation of the positive coefficient of *Profitability* is that highly profitable firms may engage in more complex financial strategies and innovative investments, including expansions, acquisitions, or market diversification, which can introduce a higher degree of uncertainty and variability in their future performance (Chemmanur, He, & Nandy, 2010). Consequently, the initial ratings for these firms might not fully capture these evolving risks, resulting in a higher observed rating inaccuracy. *Leverage* also shows a positive and significant coefficient, indicating that more leverage firms may experience higher rating inaccuracies, potentially due to the increased financial risk and instability associated with higher debt levels (Andrade and Kaplan,1998; Faulkender & Petersen, 2006). The coefficient for $Trust_{RA,CEO}$ remains significant (-0.025, t-statistic = -6.481), reinforcing the negative relationship between trust and rating inaccuracy.

Column [4] incorporates pair-level controls, such as Cultural Distance and Difference Gender, which reflect the relational dynamics between the CEO and the rating analyst. The inclusion of these controls is crucial because our main variable, $Trust_{RA,CEO}$, is also a pair-level variable. The negative coefficients for *Cultural Distance* and *Difference Gender* highlight the importance of personal and cultural alignment in the rating process. *Cultural Distance*, which measures the average cultural distance score between the RA and CEO, indicates that greater cultural similarity facilitates better communication and understanding, leading to more

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

accurate initial ratings. This is because shared cultural norms and values can enhance mutual trust and reduce misinterpretations (Guiso et al., 2009). Similarly, the negative coefficient for *Difference Gender* suggests that gender differences may introduce additional barriers to effective communication and trust (Huang & Kisgen, 2013). This can result in less accurate initial ratings due to potential biases or misunderstandings, necessitating more frequent subsequent adjustments. Therefore, aligning the cultural and personal attributes between RAs and CEOs can play a crucial role in improving rating accuracy. After adding three groups of control variables of different levels, the coefficient for $Trust_{RA,CEO}$ slightly increases in magnitude to -0.030 (t-statistic = -6.656) and remains highly significant.

Through Table 2, we validate Hypothesis 1a: higher levels of trust from RAs to CEOs are associated with more accurate credit ratings. In complex and dynamic financial markets, RAs face a massive amount of information, including noisy information that is difficult to verify directly despite potentially containing valuable content. This type of information is often selectively ignored by RAs in their routine analysis process due to its high verification costs. However, the results of Table 2 highlight an important factor—trust. Specifically, when RAs have a high level of trust in the CEO, they are more likely to go beyond traditional validation boundaries and choose to believe in the potentially useful content within the unverified, noisy information. This trust motivates RAs to interpret the information provided by the CEO with a more open and inclusive attitude, even if the information does not seem clear or complete. In this way, RAs with higher levels of trust can identify and utilize valuable signals that other analysts may have missed due to difficulty in verification, thus improving the accuracy of credit ratings.

In summary, the baseline results demonstrate that higher trust from the rating analyst to the CEO leads to lower rating inaccuracy, with significance after including bond-level, firm-level, and pair-level controls. This section highlights trust's critical role in enhancing credit ratings' accuracy, providing a strong foundation for further cross-sectional analyses.

4.2 Cross-sectional Analysis

In this section, we conduct several cross-sectional tests to validate the causal relationship between trust and rating accuracy and pin down the economic mechanism of such a causal relationship. We center our cross-sectional analysis around the information production difficulty and the firm's information environment. Specifically, we investigate how the information production ability of the rating analyst, the managerial information quality, the difficulty of information production, and the information environment influence this relationship. For all cross-sectional tests through Tables 3 to 6, the dependent and independent variables are the same as the baseline regression in Table 2.

4.2.1 RA Information Production Ability

Trust plays a role in deciding whether to accept a signal when an analyst produces a rating. If trust can indeed affect rating accuracy, when analysts are less capable of verifying information, high trust will make them more likely to rely on wrong signals than more capable analysts. Therefore, we would observe trust has a stronger effect on rating accuracy for more experienced analysts. The results in Table 3 demonstrate that for more experienced analysts, the role of trust is enhanced, as they are more capable of discerning valuable content from noisy information, and trust facilitates this process.

Table 3 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, focusing on the information production ability of the rating analyst. Table 3 re-estimates the baseline OLS regression model from Column [4] of Table 2. Columns [1], [2], and [3] report the results of cross-sectional tests for three different rating analyst ability characteristics: *RA Seniority*, *RA Experience*, and *RA Working Year*, respectively. *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 0 for junior to mid-level positions (corresponding to Analyst, Senior Analyst, and Senior Credit Officer). Column [1] shows the interaction term $Trust_{RA,CEO}$ × *RA Seniority* is significantly negative (-0.035, t-statistic = -5.487), indicating that trust has a stronger effect (i.e., reduces inaccuracy more) for senior analysts. This implies that trust is particularly beneficial when analysts have more experience and authority, possibly because senior analysts can leverage their trust in the CEO more effectively to gather more accurate information.

RA Experience is the number of reports written by Moody's rating analysts during the sample period from 2000 to 2023, divided by 100. The interaction term $Trust_{RA,CEO}$ × *RA*

Experience in column [2] is also significantly negative (-0.009, t-statistic = -2.621), suggesting that more experienced analysts can better utilize trust in the CEO to enhance rating accuracy. This supports the idea that experienced analysts are more adept at using interpersonal trust to gather valuable insights. *RA Working Year* is the logarithm of 1 plus the number of years Moody's rating analyst has worked during the sample period. Column [3] examines the interaction with *RA Working Year*, which shows a slightly less pronounced but still significant negative interaction (-0.005, t-statistic = -1.774). This indicates that longer tenure analysts can utilize trust to enhance rating accuracy, though to a lesser extent than seniority and experience.

The finding in Table 3 resonates with prior research asserting that trust can mitigate information asymmetry between individuals (Duarte et al., 2012; Bottazzi et al., 2016). In credit ratings, the rating analyst's report-writing process serves as information production, and trust facilitates a reduction in asymmetry between RAs and CEOs, ultimately yielding more precise ratings. Notably, the positive effect of trust is contingent upon the analyst's proficiency in processing and leveraging CEO-provided information. Senior and experienced analysts better use trust in their interactions with CEOs, enhancing their expertise and minimizing rating inaccuracies, while less experienced analysts may struggle due to comprehension limitations. Thus, trust's advantage is most pronounced among analysts with advanced information processing skills.

4.2.2 Managerial 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 4 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: *Discretionary Accruals* and *Fraud Restatement*. *Discretionary 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 *Discretionary Accruals* is significantly positive (0.101, t-statistic = 2.929). 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. *Fraud 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 $Trust_{RA,CEO} \times Fraud\ Restatement$ is also significantly positive (0.040, t-statistic = 3.555). This indicates that in firms with a history of fraud, $Trust_{RA,CEO}$ increases rating inaccuracy.

The findings in Table 4 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.

4.2.3 Information Production Difficulty

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 5 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 $Trust_{RA,CEO}\times$ Geographical Distance is significantly negative (-0.005, t-statistic = -2.211), 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 $Trust_{RA,CEO}\times$ *Flight Distance* is also significantly negative (-0.004, t-statistic = -1.759), 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 (-0.000, t-statistic = -2.101). 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.

4.2.4 Information Environment

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 6 investigates how the broader information environment influences the trust-rating accuracy relationship. Columns [1] and [2] report the results of cross-sectional tests for two different information environment characteristics: *Analyst Coverage* and *Media Coverage*. Media Coverage is the logarithm of 1 plus the number of media reports fully relevant to the bond issuer's firm. Column [1] shows the interaction term $Trust_{RA,CEO} \times$ *Media Coverage* being significantly positive (0.024, t-statistic = 6.532). The results in Table 6 suggest that in environments with high media coverage, the reliance on trust might be reduced, as external information sources provide sufficient information for rating accuracy. *Analyst Coverage* is the logarithm of 1 plus the number of analysts covering the bond issuer's firm. The interaction term $Trust_{RA,CEO} \times$ *Analyst Coverage* in column [2] is also significantly positive (0.028, t-statistic = 4.296). This indicates that trust between the RA and CEO is less critical in firms with high analyst coverage, as external analysts' reports provide additional layers of scrutiny and information, thus reducing the necessity of trust for accurate ratings.

The results in Table 6 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.

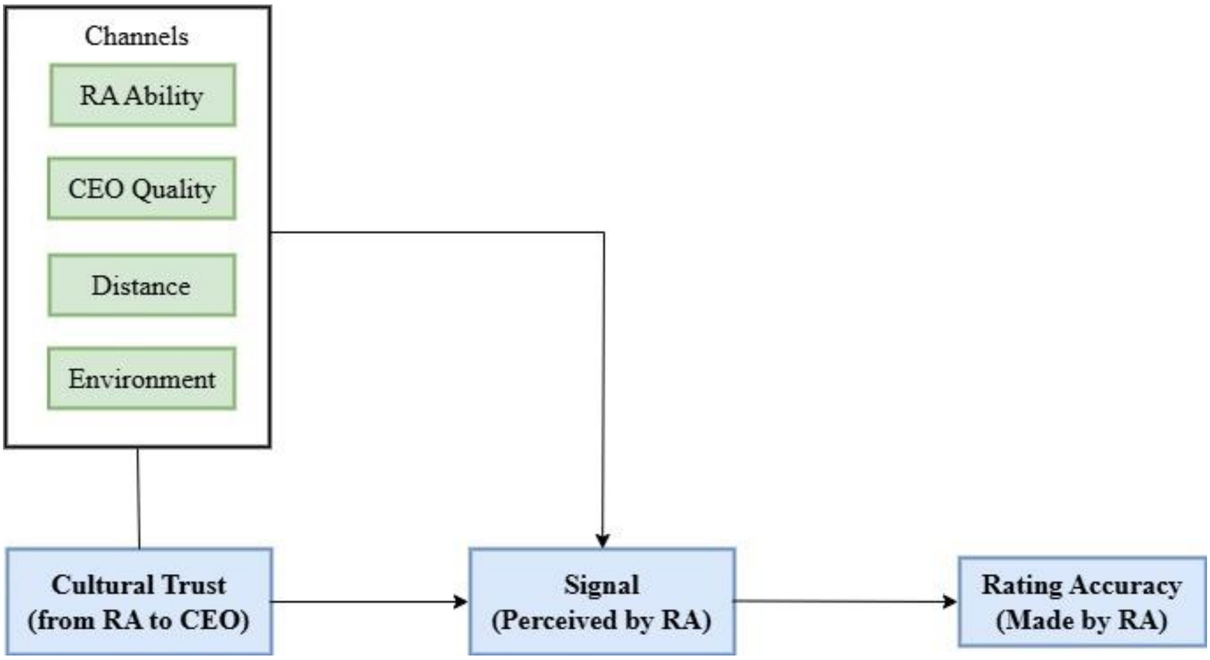

Figure 2. Channels Influencing the Impact of Cultural Trust on Rating Accuracy

As Figure 2 shows, trust is influenced by factors such as the analyst's ability to interpret information, the information quality released by the CEO, the distance between the CEO and analyst, and the broader information environment. This trust, in turn, affects how analysts perceive and utilize the signals from CEOs, ultimately influencing the credit rating accuracy. The results in Tables 3 through 6 illustrate trust generally improves rating accuracy, especially when managerial information quality is high, analysts are experienced, and external information is limited. Conversely, trust may not enhance rating accuracy when information quality is poor or external information is abundant.

Specifically, Table 3 highlights that experienced rating analysts are better equipped to leverage trust in their interactions with CEOs, enabling them to discern valuable information from noisy data and ultimately improve rating precision. This finding aligns with research on trust mitigating information asymmetry. Table 4 underscores the critical role of management information quality, revealing that low-quality signals from management can distort the information environment and undermine the positive effect of trust on rating accuracy. Signaling theory provides a theoretical foundation for this observation. Table 5 supports social capital theory by demonstrating that trust can bridge communication gaps, particularly when physical distance limits face-to-face interactions. Trust is a substitute for physical proximity, facilitating the flow of information necessary for accurate ratings. Finally, Table 6 shows that the marginal value of trust decreases in information-rich environments, where abundant external sources allow rating analysts to cross-verify data and reduce reliance on single information sources. In summary, while trust plays a significant role in enhancing rating accuracy, its impact varies based on analysts' experience, management information quality, and the availability of external information.

4.3 Trust, Bond Rating, and Bond Covenant

Table 7 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). *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. 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 (2.881, t-statistic = 0.729), 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 (-0.006, t-statistic = -2.825), 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 (1.388, t-statistic = 1.276) or Bond Covenants (-0.000, t-statistic = -0.337), 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 7 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 7 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 Robustness Checks

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 employed alternative inaccuracy measures to verify our findings' consistency across different definitions and time frames. Third, we used various alternative trust measures to confirm that our results are not dependent on a single trust metric. Finally, we applied different clustering methods to test the robustness of our results against potential biases introduced by the clustering choices. These robustness checks collectively reinforce the reliability and validity of our findings.

4.4.1 Endogeneity Issue

In addressing potential endogeneity concerns, it is essential to consider the possibility of reverse causality, where rating agencies might assign trusted rating analyst to firms based on their CEOs' perceived trustworthiness. However, this scenario is less likely due to several reasons. Firstly, the assignment of RAs to firms is typically based on organizational guidelines and workload distribution rather than the trust level between the RA and the CEO. Rating agencies like Moody's follow standardized procedures to ensure objectivity and independence in their assessments, minimizing subjective factors such as personal trust (Kisgen et al., 2020). Secondly, the trust measures used in our study are derived from long-standing cultural and social trust indicators, which are not easily manipulable or influenced by the short-term strategic decisions of rating agencies or firms. Lastly, the primary determinants of RA assignments are often related to the industry expertise and analytical skills of the analysts, which are crucial for maintaining the credibility and accuracy of the ratings. By considering these factors, we mitigate the concern of reverse causality, reinforcing the validity of our findings that higher trust levels from RAs to CEOs lead to improved rating accuracy.

To alleviate omitted variable bias concerns, Table 8 incorporates additional controls and fixed effects to validate the robustness of our findings. In Column [1], we include the trust level from the CEO to the RA, $Trust_{CEO,RA}$, which represents the trust level from the issuer's CEO to the Moody's rating analyst. This variable is highly correlated with $Trust_{RA,CEO}$ but captures the trust perspective from the opposite direction. The significant negative coefficient (-0.017, t-statistic = -2.492) indicates that CEO trust in the RA also contributes to lower rating inaccuracy, reinforcing the importance of mutual trust in enhancing rating accuracy. The coefficient for $Trust_{RA,CEO}$ remains negative and significant (-0.017, t-statistic = -2.360), indicating that our main findings are robust even when considering the reciprocal trust relationship.

In Column [2], we included four dimensions of cultural distance based on Hofstede's cultural dimensions: *Cultural Distance MAS* (Masculinity vs. Femininity), *Cultural Distance UAI* (Uncertainty Avoidance Index), *Cultural Distance PDI* (Power Distance Index), and

Cultural Distance IDV (Individualism vs. Collectivism). The results show that *Cultural Distance MAS* has a positive and significant coefficient (0.008, t-statistic = 1.901), higher masculinity distance, which emphasizes competitiveness and achievement, may reduce rating accuracy when trust is considered. Conversely, the negative coefficients for *Cultural Distance UAI* (-0.021, t-statistic = -2.506) and *Cultural Distance PDI* (-0.018, t-statistic = -2.453) suggest that larger differences in these cultural dimensions between the RA and CEO are associated with lower rating inaccuracy, meaning higher rating accuracy. *UAI* index measures how comfortable a culture is with uncertainty and ambiguity. If the RA and CEO have very different levels of comfort with uncertainty (high cultural distance in *UAI*), it can help in creating a more balanced perspective. For example, an RA from a culture that is more comfortable with uncertainty might challenge the conservative strategies of a CEO from a high *UAI* culture, leading to more thorough assessments and accurate ratings. *PDI* index measures how much a culture values hierarchy and unequal power distribution. When the RA and CEO come from cultures with different attitudes toward hierarchy (high cultural distance in *PDI*), it can create a dynamic where the RA is more independent in their assessments, potentially questioning and verifying information more rigorously. This can relate to more accurate ratings as the RA does not simply accept information from a hierarchical superior at face value. Therefore, larger differences in these cultural dimensions between the RA and CEO seem to facilitate a more critical and balanced approach to information assessment, leading to higher rating accuracy.

Column [3] introduces three additional RA characteristics: *RA Seniority*, *RA Experience*, and *RA Working Year*. 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 (-0.030, t-statistic = -6.786), confirming that our findings are not driven by variations in analysts' characteristics. Notably, *RA Experience* is significant and negative (-0.014, t-statistic = -2.168), implying that more experienced analysts might produce more accurate ratings due to their enhanced ability to process information and make accurate assessments over time.

In Column [4], we included CEO fixed effects to control for CEO-specific heterogeneity. The coefficient of $Trust_{RA,CEO}$ remains significantly negative (-0.021, t-statistic = -3.560), indicating that the trust effect persists even when accounting for unobserved CEO characteristics. Column [5] replaces firm and year fixed effects with firm-year fixed effects to comprehensively control for time-varying firm-specific factors. The coefficient of $Trust_{RA,CEO}$

remains significantly negative (-0.014, t-statistic = -2.391), suggesting that our main findings are robust to these alternative specifications.

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

4.4.2 Alternative Measures of Inaccuracy

To further establish the robustness of our findings, we employed several alternative measures of rating inaccuracy, as summarized in Table 9. 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 $Inaccuracy_{6m}$, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within six months. The negative and significant coefficient (-0.013, t-statistic = -3.962) indicates that higher trust is associated with lower rating inaccuracy even when the revision period is shortened to six months. This suggests that trust leads to more accurate initial ratings, reducing the need for subsequent revisions within a shorter timeframe. Column [2] explores $Inaccuracy_{2y}$, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within two years. The negative and significant coefficient (-0.080, t-statistic = -5.980) remains, suggesting that the effect of trust on reducing rating inaccuracy is robust over a longer period, reinforcing the idea that trust contributes to long-term accuracy in bond ratings. In column [3], we use $Inaccuracy_{dum}$, a binary variable indicating whether Moody's initial bond rating has changed within one year. The negative and significant coefficient (-0.043, t-statistic = -7.439) 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.

Columns [4] and [5] focus on the relative performance of Moody's ratings compared to S&P's ratings. Following the methodology of Kisgen et al. (2020), we design two alternative rating accuracy measures as $Leading_{dum}$ and $Leading_{cont}$. These measures serve as a reasonable alternative to our baseline inaccuracy measure. While the baseline measure examines changes in Moody's own ratings, the leading measures observe changes relative to a peer rating agency, S&P. Specifically, we focus on instances where S&P and Moody's publish different ratings for the same firm at the same time. Column [4] employs the dependent variable as $Leading_{dum}$, a binary variable indicating whether S&P subsequently adjusts its rating toward Moody's initial rating within one year. The positive and significant coefficient (0.031, t-statistic = 1.938) suggests that higher trust increases the likelihood that Moody's rating leads to S&P's rating. This implies that trust contributes to rating accuracy and positions Moody's ratings as timely and potentially more informative. Column [5] uses $Leading_{cont}$, which measures the extent to which S&P adjusts its rating in the direction of Moody's rating within one year. The positive and significant coefficient (0.044, t-statistic = 2.244) indicates that higher trust enhances the extent to which Moody's ratings influence subsequent changes in S&P's ratings. This refined measure captures whether S&P's ratings align with Moody's and the degree of alignment or divergence.

The robustness of our findings in Table 9 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 results for the $Leading_{dum}$ and $Leading_{cont}$ variables suggest 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.

4.4.3 Alternative Measures of Trust

This subsection examines the robustness of our findings by using various alternative measures of trust between the rating analyst and the CEO (or CFO). Table 10 presents the results of these robustness tests. The dependent variable in all models is Inaccuracy, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. We explore five alternative trust measures to ensure our results are consistent across different trust constructs.

In Column [1], the independent variable $Trust_{TotalRA,CEO}$, which measures the trust level between the CEO and all Moody's rating analysts, including both primary and secondary RAs. As we mentioned in Section 3.3, we manually collected rating announcements signed by analysts. Typically, these announcements list one or two analysts. We define the primary RA as the first or most senior RA listed on the report, as this person is considered to play a dominant role in the decision-making process. To consider whether the second RA also plays a role, we created variables $Trust_{TotalRA,CEO}$ that take the mean of the two RAs. This measure is also calculated based on the three countries with the most frequent origins associated with primary RA and secondary RA surnames and the level of trust between these countries. The negative and significant coefficient (-0.009, t-statistic = -1.958) suggests that including secondary RAs in the trust measure still supports the finding that higher trust between RAs and the CEO is associated with lower rating inaccuracy.

We discuss in detail in Subsection 3.3 how the *Ancestry.com* database can be used to infer the country of origin of the surname, and it has the advantage of being able to calculate the proportions of the different national origins by distribution. We selected the three most common countries of origin of the investigators' surnames to match in the baseline regression. For the robustness of the research, we created $Trust_{CEO,RA}(one\ orgin\ country)$ to observe the selection of the main country of origin of the investigator's surname (unique and with the weight of this country of origin accounting for more than 50% of the total weight). Column [2] uses $Trust_{CEO,RA}(one\ orgin\ country)$, calculated based on the most frequent and dominant origin country associated with their surnames and the level of trust between these countries. The negative and significant coefficient (-0.015, t-statistic = -3.366) indicates that trust still enhances rating accuracy even with a more restrictive definition of origin. In column [3], $Trust_{CEO,RA}(all\ orgin\ country)$ considers all origin countries (weighted) associated with their surnames and the level of trust between these countries. The negative and significant coefficient (-0.032, t-statistic = -6.843) further confirms the robustness of our results, showing that trust remains a significant factor in reducing rating inaccuracy when considering a more comprehensive measure of origin countries.

Column [4] examines whether or not the CFO also plays the role. The independent variable is $Trust_{RA,CFO}$, measuring the trust level between the CFO and Moody's rating analyst, excluding the CEO. The positive but not significant coefficient (0.009, t-statistic = 0.891) suggests that trust between the RA and CFO does not significantly impact rating inaccuracy. This indicates that the CEO's role in conveying accurate information to the RA is more crucial than the CFO's role. Finally, column [5] uses $Trust_{RA,CEO\&CFO}$, which measures the combined trust level between both the CEO and CFO and Moody's rating analyst. The negative and significant coefficient (-0.174, t-statistic = -5.561), indicates that when trust is measured inclusively between the rating analyst and the top management team, the relationship with rating accuracy becomes even stronger.

In summary, the significant results for various trust measures suggest that the robustness of the trust-inaccuracy relationship is not dependent on a specific way of calculating trust. Whether trust is measured based on the primary RA, secondary RA, or both, and whether it is calculated using one or multiple origin countries, the overall impact of trust on reducing rating inaccuracy remains consistent.

4.4.4 Alternative Clustering Methods

Table 11 presents the baseline OLS regression model with standard errors clustered at various levels to assess the robustness of our results to different clustering methods. Column [1] clusters standard errors by the firm, while Column [2] clusters by rating analyst (RA). Columns [3] and [4] use dual clustering methods, clustering by both firm and year, and by both rating analyst and year, respectively. The results indicate that the coefficient for $Trust_{RA,CEO}$ remains negative and significant across all clustering methods, though the significance level varies slightly. Table 9 suggests that our findings are robust to different methods of clustering standard errors, further confirming the reliability of our main results. In summary, these robustness checks collectively strengthen the validity of our results of the trust-rating accuracy relationship across various model specifications.

5. Conclusion

This study provides valuable insights into trust from rating analysts to CEO in influencing the accuracy of credit ratings. The main finding of our research is that higher levels of trust relate to higher rating accuracy. Trust facilitates better information exchange and helps rating analysts identify and utilize valuable information within the noise. Various cross-sectional tests demonstrate that RA's trust in the CEO improves rating accuracy when managerial information quality is high, analysts are experienced, and external information is limited. Specifically, trust is beneficial for experienced analysts who can discern valuable content from noisy information and when external information is scarce, necessitating reliance on internal sources. However, the positive impact of trust is contingent upon the quality of the information provided by management; when management information quality is low, trust is associated with over-reliance on misleading signals, thereby exacerbating rating inaccuracies. Additionally, in information-rich environments with ample media and analyst coverage, the marginal value of trust diminishes as external information sources provide sufficient means for verification. These findings underscore the nuanced role of trust in financial decision-making and its varying impact based on contextual factors, contributing to a deeper understanding of the mechanisms that influence rating accuracy in the credit rating industry.

Despite its contributions, this study has limitations. The measurement of trust based on surname origins may not fully capture the nuanced and dynamic 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.

The findings have important policy implications for CARs and regulatory bodies. CRAs should closely monitor the cultural trust between rating analysts and CEOs, as this trust can have varying effects depending on the information environment. Specifically, while trust can enhance rating accuracy in high-quality information environments, it may lead to biased or inaccurate ratings when information quality is poor. Therefore, CRAs need to balance the use of culturally trusted RAs with the potential for access to information and the risk of inaccurate ratings. The objective should be to ensure accurate ratings, especially in poor information environments. Regulators should ensure that mechanisms are in place to prevent trust from leading to complacency or biased ratings, thereby safeguarding the integrity of credit ratings even in less favorable information environments.

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Table 1. Descriptive Statistics

This table provides summary statistics for the bond-issue-level observations in the sample, which includes 10,955 issuances by 929 firms in the U.S. primary bond market from 2000 to 2023. *Inaccuracy* is measured as the absolute difference (in notches) between Moody's initial bond rating and the revision rating within one year. $Trust_{RA,CEO}$ represents 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. Detailed variable definitions are available in Appendix A.

	N [1]	*Mean* [2]	*Std. Dev.* [3]	*Min* [4]	*Median* [5]	*Max* [6]
Inaccuracy	10,955	0.016	0.160	0	0	6
$Trust_{RA,CEO}$	10,955	0	1	-2.511	-0.051	1.974
Bond Rating	10,955	16.605	4.829	2	17	21
Ln (No. of Issuance)	10,955	5.330	3.010	0	5.700	9.44
R144A	10,955	0.086	0.280	0	0	1
Callable	10,955	0.987	0.112	0	1	1
Profitability	10,955	0.023	0.017	-0.012	0.017	0.084
MTB	10,955	1.444	0.764	0.782	1.093	5.507
Tangibility	10,955	0.164	0.244	0	0.013	0.891
Leverage	10,955	0.548	0.346	-0.227	0.560	0.929
Size	10,955	5.678	1.478	1.276	6.728	6.728
Cultural Distance	10,955	0	1	-1.204	-0.297	3.99
Difference Gender	10,955	0.471	0.499	0	0	1

Table 2. Rating Inaccuracy and Trust

This table presents the Ordinary Least Squares (OLS) regression results examining the impact of trust from the rating analyst to the CEO on bond rating accuracy. The dependent variable is *Inaccuracy*, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. Detailed definitions of all control variables are provided in Appendix A. All models include the firm fixed effects, year fixed effects, and rating analyst fixed effects. The t-statistics are reported in parentheses. 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]
$Trust_{RA,CEO}$	-0.025***	-0.025***	-0.025***	-0.030***
	(-6.445)	(-6.387)	(-6.481)	(-6.656)
Bond Rating		0.004	0.003	0.004
		(0.814)	(0.614)	(0.647)
Ln (No. of Issuance)		-0.016***	-0.017***	-0.016***
		(-3.291)	(-3.403)	(-3.311)
R144A		-0.030***	-0.029***	-0.029***
		(-3.170)	(-3.050)	(-3.067)
Callable		-0.032	-0.031	-0.030
		(-0.729)	(-0.714)	(-0.700)
Profitability			0.838***	0.855***
			(3.887)	(3.963)
MTB			0.006	0.006
			(1.077)	(1.010)
Tangibility			-0.112	-0.114
			(-1.133)	(-1.148)
Leverage			0.071*	0.077**
			(1.886)	(2.010)
Size			0.017	0.015
			(1.371)	(1.175)
Cultural Distance				-0.011***
				(-2.870)
Difference Gender				-0.018**
				(-2.334)
Firm F.E.s	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes
RA F.E.s	Yes	Yes	Yes	Yes
N	10,955	10,955	10,955	10,955
Adj. R^2	0.437	0.440	0.441	0.442

Table 3. Cross-sectional Test: RA Information Production Ability

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, with a focus on the information production ability of the rating analyst. The dependent variable is *Inaccuracy*, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. Table 3 re-estimates the baseline OLS regression model from Column [4] of Table 2. Columns [1], [2], and [3] report the results of cross-sectional tests for three different rating analyst ability characteristics: *RA Seniority*, *RA Experience*, and *RA Working Year*, respectively. *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. *RA Working Year* is the logarithm of 1 plus the number of years Moody's rating analyst has worked during the sample period. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var. = Inaccuracy	[1]	[2]	[3]
$Trust_{RA,CEO}$	-0.013***	-0.015**	-0.021***
	(-3.018)	(-2.468)	(-3.216)
RA Seniority	-0.017		
	(-1.498)		
$Trust_{RA,CEO}$ × *RA Seniority*	-0.035***		
	(-5.487)		
RA Experience		-0.016**	
		(-2.524)	
$Trust_{RA,CEO}$ × *RA Experience*		-0.009***	
		(-2.621)	
RA Working Year			0.012
			(0.998)
$Trust_{RA,CEO}$ × *RA Working Year*			-0.005*
			(-1.774)
Controls	Yes	Yes	Yes
Firm F.E.s	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes
RA F.E.s	Yes	Yes	Yes
N	10,944	10,944	10,944
Adj. R^2	0.445	0.444	0.442

Table 4. Cross-sectional Test: Managerial Information Quality

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 managerial information quality. The dependent variable is *Inaccuracy*, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. Table 4 re-estimates the baseline OLS regression model from Column [4] of Table 2. Columns [1] and [2] report the results of cross-sectional tests for two managerial information quality characteristics: *Discretionary Accruals* and *Fraud Restatement*. *Discretionary Accruals* are calculated using the Kothari Model, which matches firms based on performance metrics such as Return on Assets (ROA). *Fraud Restatement* is the number of fraud restatements of the firm in the year before the rating release. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var. = Inaccuracy	[1]	[2]
$Trust_{RA,CEO}$	-0.042***	-0.030***
	(-7.085)	(-6.731)
Discretionary Accruals	-0.064	
	(-1.622)	
$Trust_{RA,CEO}$ × *Discretionary Accruals*	0.101***	
	(2.929)	
Fraud Restatement		0.046*
		(1.864)
$Trust_{RA,CEO}$ × *Fraud Restatement*		0.040***
		(3.555)
Controls	Yes	Yes
Firm F.E.s	Yes	Yes
Year F.E.s	Yes	Yes
RA F.E.s	Yes	Yes
N	10,107	10,944
Adj. R^2	0.241	0.442

Table 5. Cross-sectional Test: Information Production Difficulty

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 difficulty of information production. The dependent variable is Inaccuracy, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. Table 5 re-estimates the baseline OLS regression model from Column [4] of Table 2. 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. *Flight Distance* is the logarithm of 1 plus the shortest flight distance between the CEO and RA offices, calculated using global historical flight data. *Flight Time* is the shortest flight time between the CEO and RA offices, estimated using global historical flight data. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var. = Inaccuracy	[1]	[2]	[3]
$Trust_{RA,CEO}$	-0.005	-0.004	0.002
	(-1.328)	(-1.181)	(0.579)
Geographical Distance	-0.005		
	(-0.549)		
$Trust_{RA,CEO}$ × *Geographical Distance*	-0.005**		
	(-2.211)		
Flight Distance		-0.003	
		(-0.352)	
$Trust_{RA,CEO}$ × *Flight Distance*		-0.004*	
		(-1.759)	
Flight Time			-0.000
			(-0.780)
$Trust_{RA,CEO}$ × *Flight Time*			-0.000**
			(-2.101)
Controls	Yes	Yes	Yes
Firm F.E.s	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes
RA F.E.s	Yes	Yes	Yes
N	4,323	4,323	4,323
Adj. R^2	0.0793	0.0791	0.0789

Table 6. Cross-sectional Test: Information Environment

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. The dependent variable is Inaccuracy, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. Table 6 re-estimates the baseline OLS regression model from Column [4] of Table 2. Columns [1] and [2] report the results of cross-sectional tests for two different information environment characteristics: *Analyst Coverage* and *Media Coverage*. *Analyst Coverage* is the logarithm of 1 plus the number of analysts covering the bond issuer's firm. *Media Coverage* is the logarithm of 1 plus the number of media reports fully relevant to the bond issuer's firm. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var. = Inaccuracy	[1]	[2]
$Trust_{RA,CEO}$	-0.126***	-0.108***
	(-7.184)	(-5.345)
Media Coverage	0.011***	
	(3.570)	
$Trust_{RA,CEO}$ × *Media Coverage*	0.024***	
	(6.532)	
Analyst Coverage		0.005
		(0.230)
$Trust_{RA,CEO}$ × *Analyst Coverage*		0.028***
		(4.296)
Controls	Yes	Yes
Firm F.E.s	Yes	Yes
Year F.E.s	Yes	Yes
RA F.E.s	Yes	Yes
N	10,285	10,412
Adj. R^2	0.495	0.425

Table 7. Trust, Bond Spread and covenants

This table presents the OLS regression results in the effect of trust from the rating analyst to the CEO on bond spread and covenants. The dependent variables are *Bond Spread*, defined as the difference between the bond offering yield and the U.S. treasury bond yield (bps), and *Bond Covenants*, defined as the count of the total number of covenants included in the bonds issued by the firm, 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. 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, $Trust_{RA,CEO}\times$ *Bond Rating*, to test the moderating effect of bond rating on the relationship between trust and the dependent variables. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	Spread [1]	Covenants [2]	Spread [3]	Covenants [4]
$Trust_{RA,CEO}$	2.881	-0.006***	-14.917	-0.004
	(0.729)	(-2.825)	(-0.962)	(-0.565)
Bond Rating	-32.554***	-0.005***	-32.221***	-0.005***
	(-11.011)	(-3.455)	(-10.794)	(-3.457)
$Trust_{RA,CEO}$ × *Bond Rating*			1.388	-0.000
			(1.276)	(-0.337)
Controls	Yes	Yes	Yes	Yes
Firm F.E.s	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes
RA F.E.s	Yes	Yes	Yes	Yes
N	3,256	10,955	3,256	10,955
Adj. R^2	0.750	0.840	0.751	0.840

Table 8. Alleviating Omitted Variable Concern

This table presents the robustness test results for the baseline OLS regression model from Column [4] of Table 2, examining the impact of trust from the rating analyst to the CEO on bond rating accuracy. The dependent variable is *Inaccuracy*, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. Table 8 includes five columns, each incorporating different robustness checks. Column [1] adds $Trust_{CEO,RA}$, is a standardized score reflecting the trust level of the issuer's CEO to Moody's rating analyst. Column [2] includes four dimensions of cultural distance: *Cultural Distance UAI*, *Cultural Distance PDI*, *Cultural Distance MAS*, and *Cultural Distance IDV*, based on Hofstede's cultural dimensions. Column [3] incorporates three dimensions of RA characteristics: *RA Seniority*, *RA Experience,* and *RA Working Year*. Column [4] includes CEO fixed effects to control for CEO-specific heterogeneity. Column [5] replaces firm and year fixed effects with firm-year fixed effects to account for time-varying firm-specific factors. All control variables are included. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. 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]	[5]
$Trust_{RA,CEO}$	-0.017**	-0.038***	-0.030***	-0.021***	-0.014**
	(-2.360)	(-7.421)	(-6.786)	(-3.560)	(-2.391)
$Trust_{CEO,RA}$	-0.017**				
	(-2.492)				
Cultural Distance MAS		0.008*			
		(1.901)			
Cultural Distance IDV		0.001			
		(0.069)			
Cultural Distance UAI		-0.021**			
		(-2.506)			
Cultural Distance PDI		-0.018**			
		(-2.453)			
RA Seniority			-0.014		
			(-1.269)		
RA Working Year			0.016		
			(1.370)		
RA Experience			-0.014**		
			(-2.168)		
Controls	Yes	Yes	Yes	Yes	Yes
Firm & Year F.E.s	Yes	Yes	Yes	Yes	No
RA F.E.s	Yes	Yes	Yes	Yes	Yes
CEO F.E.s	No	No	No	Yes	No
Firm × Year F.E.	No	No	No	No	Yes
N	10,903	10,955	10,944	10,955	10,955
Adj. R^2	0.442	0.444	0.442	0.483	0.802

Table 9. Alternative Measures of Inaccuracy

This table presents the robustness test results using alternative measures of inaccuracy in bond ratings. The dependent variable is *Inaccuracy*, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. The table explores five alternative measures of inaccuracy: $Inaccuracy_{6m}$ measured as the absolute difference (in notches) between Moody's initial bond rating and the revision rating within six months. $Inaccuracy_{2y}$ measured as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within two years. $Inaccuracy_{dum}$ measured as a binary variable indicating whether Moody's initial bond rating has changed within one year. $Leading_{dum}$ measured as a binary variable indicating whether Moody's initial bond rating leads to S&P's bond rating within one year. $Leading_{cont}$ measured as the extent to which Moody's initial bond rating leads S&P's bond rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. Significance levels are indicated by ***, **, and *, corresponding to statistical significance at the 1%, 5%, and 10% levels, respectively.

	[1]	[2]	[3]	[4]	[5]
Dep. Var.	$Inaccuracy_{6m}$	$Inaccuracy_{2y}$	$Inaccuracy_{dum}$	$Leading_{dum}$	$Leading_{cont}$
$Trust_{RA,CEO}$	-0.013***	-0.080***	-0.043***	0.031*	0.044**
	(-3.962)	(-5.980)	(-7.439)	(1.938)	(2.244)
Controls	Yes	Yes	Yes	Yes	Yes
Firm F.E.s	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes
RA F.E.s	Yes	Yes	Yes	Yes	Yes
N	10,955	10,955	10,955	2,256	2,256
Adj. R^2	0.313	0.673	0.241	0.627	0.624

Table 10. Alternative Measures of Trust

This table presents the robustness test results using alternative trust measures in the relationship between the rating analyst and the CEO (or CFO). The dependent variable is *Inaccuracy*, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. The table explores five alternative measures of trust. $Trust_{TotalRA,CEO}$ measured as a standardized score measuring the trust level between the CEO and Moody's rating analyst, including both primary and secondary RAs (baseline only includes primary RA). This measure is calculated based on the three most frequent origin countries associated with their surnames and the level of trust between these countries. $Trust_{CEO,RA}(one\ orgin\ country)$ is calculated based on the most frequent origin country (dominant one, weight 50% or higher) associated with their surnames and the level of trust between these countries. $Trust_{CEO,RA}(all\ orgin\ country)$ is calculated based on all origin countries (weighted) associated with their surnames and the level of trust between these countries. $Trust_{RA,CFO}$ measuring the trust level between the CFO and Moody's rating analyst, which the sample excludes the CEO. $Trust_{RA,CEO\&CFO}$: Measuring the trust level between both the CEO and CFO and Moody's rating analyst. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. 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]	[5]
$Trust_{TotalRA,CEO}$	-0.009*				
	(-1.958)				
$Trust_{CEO,RA}(one\ orgin\ country)$		-0.015***			
		(-3.366)			
$Trust_{CEO,RA}(all\ orgin\ country)$			-0.032***		
			(-6.843)		
$Trust_{RA,CFO}$				0.009	
				(0.891)	
$Trust_{RA,CEO\&CFO}$					-0.174***
					(-5.561)
Controls	Yes	Yes	Yes	Yes	Yes
Firm F.E.s	Yes	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes	Yes
RA F.E.s	Yes	Yes	Yes	Yes	Yes
N	10,955	10,955	10,955	8,652	11,498
Adj. R^2	0.438	0.438	0.442	0.470	0.399

Table 11. Alternative Clustering Methods

This table presents the robustness test results for the baseline OLS regression model, examining the impact of trust from the rating analyst to the CEO on bond rating accuracy using different clustering methods for standard errors. The dependent variable is *Inaccuracy*, defined as the absolute difference (in notches) between Moody's initial bond rating and the revised rating within one year. 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. This trust measure is calculated based on the three most frequent origin countries associated with their surnames and the corresponding trust levels between these countries. Table 9 includes four columns, each applying a different clustering method: Column [1] clusters by firm. Column [2] clusters by rating analyst (RA). Column [3] clusters by both firm and year. Column [4] clusters by both rating analyst (RA) and year. All models include the same set of control variables, firm fixed effects, year fixed effects, and rating analyst fixed effects. Detailed definitions of all variables are provided in Appendix A. The t-statistics are reported in parentheses. 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]
Cluster by	*Firm*	*RA*	*Firm&Year*	*RA&Year*
$Trust_{RA,CEO}$	-0.030**	-0.030**	-0.030*	-0.030*
	(-2.084)	(-2.123)	(-1.824)	(-1.761)
Controls	Yes	Yes	Yes	Yes
Firm F.E.s	Yes	Yes	Yes	Yes
Year F.E.s	Yes	Yes	Yes	Yes
RA F.E.s	Yes	Yes	Yes	Yes
N	10,955	10,955	10,955	10,955
Adj. R^2	0.440	0.440	0.440	0.440

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. $Inaccuracy\_level_{j,t} = \frac{1}{N-1}\sum_{k=1}^{N-1}\lvert R_{j,t_k} - R_{j,t_0}\rvert$	Mergent FISD
$Trust_{RA,CEO}$	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. $Trust_{i\rightarrow j} = \sum_{C1=1}^{3}\sum_{C2=1}^{3} P_{i,C1}\, P_{j,C2} Trust_{C1\rightarrow C2}$	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(No. of Issuance)	Logarithm of 1 plus firm's issuance experience in the primary market over the sample period (2000-2023).	Mergent FISD
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
Cultural Distance 4	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 dimensions (IDV, UAI, PDI, MAS).	Hofstede (2001); *Ancestry*

Difference 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
Media Coverage	The logarithm of 1 plus the number of media coverages for the bond issuer's firm, considering only media reports that are fully relevant to the firm.	RavenPack
Analyst Coverage	The logarithm of 1 plus the number of analyst coverages for the bond issuer's firm.	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
RA Working Year	Logarithm of 1 plus the number of years Moody's rating analyst has worked, during the sample period from 2000 to 2023.	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
Discretionary 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.	
Fraud Restatement	Number of fraud restatements of the firm in the year before the rating release.	
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	Hofstede (2001)

	between the RA and the CEO, based on Hofstede's cultural dimensions.	
Cultural Distance IDV	The difference in Individualism (IDV) scores between the RA and the CEO, based on Hofstede's cultural dimensions.	Hofstede (2001)
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	-527	-8,941
Final Sample	**929**	**10,955**