

ESG integration, information asymmetry, and credit risk uncertainty

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Abstract

This paper examines the economic consequences of incorporating environmental, social, and governance (ESG) information into credit ratings. Exploiting the staggered adoption of ESG information by major credit rating agencies (CRAs) following their signing of the UN Principles for Responsible Investment (PRI) ESG in Credit Risk and Ratings Statement, we find that ESG integration significantly reduces rating disagreements between CRAs. This effect is more pronounced in firms with high information asymmetry and greater political uncertainty. Furthermore, we document an economically meaningful reduction in borrowing costs, as firms with superior ESG disclosure profiles experience an average credit spread reduction of approximately 4%.

Keywords: Information asymmetry, ESG disclosure, credit rating disagreement, UNPRI

JEL classification: G12, G24

1. Introduction

The increasing prominence of sustainable finance has heightened the relevance of non-financial information, particularly Environmental, Social, and Governance (ESG) factors, in financial markets¹. This issue has gained greater significance amid recent political debates over “woke capitalism” and the growing anti-ESG sentiments². While theoretical models suggest that ESG influences economic decisions³, empirical findings remain inconclusive regarding their consequences⁴. These divergent findings may stem from differences in ESG measurement, sample selection, and methodological approaches (e.g., Berg, Kölbel, and Rigobon 2022; Christensen, Serafeim, and Sikochi 2022; Li, Lou, and Zhang 2024). This mixed evidence underscores the importance of examining settings where the informational value of ESG can be more clearly identified. We therefore turn to the fixed income market—a context that demands particularly precise information processing to avoid losses—to investigate the role of ESG information in credit risk assessment.

This paper re-examines the impact of ESG information through the lens of credit rating agencies (CRAs) while remaining agnostic about specific ESG metrics and channels through which ESG information is incorporated. We propose two contrasting hypotheses: if ESG information is value-relevant and CRAs are better positioned to aggregate and process it, their integration of this

1 Thomson Reuters Institute (2024) highlights 82% of executives acknowledge the increasing role of ESG (Environmental, Social, and Governance) in corporate strategy and financial decision-making

2 ESG investing backlash continues and ESG fund outflow hit record high: <https://www.ft.com/content/9f425c25-4fc3-45de-bcc5-e9c75d6d14d3>

3 For theoretical perspectives on ESG’s role in financial decisions, see Pástor, Stambaugh, and Taylor (2022); Bond and Levit (2025); Chowdhry, Davies, and Waters (2019); Oehmke and Opp (2025).

4 Some studies show that ESG considerations significantly affect financial and real outcomes (e.g., Dhaliwal et al. 2011; Chava 2014; Flammer 2015; Lys, Naughton, and Wang 2015; Naughton et al., 2019; Tomar 2023), whereas others find results are conditional or with limited impact (e.g., Khan, Serafeim, and Yoon 2016; Avramov et al. 2022; Zhang 2025).

information could reduce issuer-CRA information asymmetry, enabling CRAs to update their priors about default risk, especially concerning prominent downside risks (Starks 2023; Hoepner et al. 2024). Conversely, if ESG disclosures are characterized by misinformation or reflected by greenwashing (Duchin, Gao, and Xu 2025) and CRAs lack the ability to separate and extract valid signals, such information may introduce noise, leading CRAs to discount it and increase credit rating uncertainty. Thus, CRAs' utilization of ESG information offers a unique setting to examine whether ESG integration ultimately mitigates or exacerbates the informational frictions inherent in credit risk assessment.

However, the main challenge in identifying the causal effects of ESG integration in the credit market is that credit rating agencies do not randomly select ESG factors to include in their rating assessment, and econometricians do not directly observe which ESG information is incorporated. To address these questions, we exploit a quasi-natural experiment: the staggered signing of the *ESG in Credit Risk and Ratings Statement* under the UN Principles for Responsible Investment (PRI) by major CRAs⁵. This PRI ESG initiative represents the first formal industry commitment requiring signatories to systematically integrate and disclose ESG factors in credit evaluations⁶. We use CRA signings as a shock to ESG integration practices by CRAs and examine their effects on credit risk assessments, and we will explain this setting in detail in Section 2.1.

⁵ Prior research has largely focused on the effects of specific ESG factors selected by researchers rather than evaluating the broader impact of ESG information on credit ratings (Tsang, Frost, and Cao 2023). This selective approach raises concerns about reverse causality and omitted variable bias, potentially undermining the robustness of empirical findings. Furthermore, the absence of a universally accepted regulatory framework for ESG disclosures further complicates ESG-related credit risk studies, exacerbating these methodological challenges.

⁶ The Principles for Responsible Investment (PRI), an independent organization established in 2006, aims to promote a sustainable global financial system through the adoption and implementation of its six principles. Prior studies, such as Gibson Brandon et al. (2022) and Kim and Yoon (2023), have treated the signing of the PRI as a significant external shock in their analyses of responsible investment behaviour. In the spirit of this approach, we design our experiment by signing the PRI ESG statement as a quasi-natural experiment.

Our empirical setting leverages a dataset of 7,012 corporate bonds issued by 557 U.S. firms. The U.S. credit market provides an ideal setting for this study, as voluntary ESG reporting creates substantial variation in corporate ESG transparency and in how credit rating agencies interpret the information. We proxy for credit risk uncertainty using bond-level rating disagreements between Moody's and Fitch, following Morgan (2002), and estimate difference-in-differences models around the timing of PRI signings. Given the staggered timing of CRA announcements regarding the incorporation of ESG information into their rating processes, we construct a sample period covering both pre- and post-ESG incorporation phases. We employ a difference-in-differences (DiD) model to assess the impact of ESG information on rating disagreements between Moody's and Fitch for the same bonds. Additionally, we investigate whether the application of ESG factors into the credit rating process affects the likelihood of Moody's assigning a higher or lower rating compared to Fitch.

Our baseline results show that ESG integration reduces rating disagreements, suggesting that structured use of ESG data by CRAs lowers uncertainty in credit assessments. We also find that ESG adoption decreases the likelihood of Moody's assigning a higher or lower rating than Fitch. These effects are robust to alternative CRA pairings and persist across various model specifications. Overall, our results indicate that CRAs, as relatively sophisticated users of financial and non-financial information, can provide a more comprehensive assessment of an entity's creditworthiness after incorporating non-financial ESG information. This finding aligns with prior literature suggesting that reliable use of non-financial information can reduce information asymmetry in financial markets (e.g., Simnett, Vanstraelen, and Chua 2009; Dhaliwal et al. 2012). However, it stands in contrast to evidence that increased ESG disclosures contribute to disparate

assessments of ESG quality among different ESG rating agencies (Christensen, Serafeim, and Sikochi 2022).

We also perform a series of robustness tests. First, to account for the discrete nature of the dependent variable (rating disagreements), we re-estimate the benchmark model using a logit specification. Second, we introduce bond fixed effects in both the OLS and logit models to control for unobserved bond-level heterogeneity. Third, we leverage the timing of S&P Global Ratings' signing of the PRI ESG Statement in May 2016 to reframe the empirical design, thereby identifying the effect of ESG integration into credit rating assessments on the rating disagreements between S&P and Fitch. And all of the above tests show consistent results that incorporating ESG information decreases credit rating uncertainty.

Moreover, since the integration of ESG factors into the bond rating process occurs at varying times across bonds, it is necessary to account for treatment effect heterogeneity and variation in treatment timing to avoid biased estimation (Borusyak, Jaravel, and Spiess, 2024). To address these concerns, we employ the two-stage difference-in-differences (2SDD) estimator proposed by Gardner et al. (2025), which yields consistent estimates in the presence of staggered and heterogeneous treatment adoption. This method removes group and period fixed effects using only untreated observations and subsequently estimates treatment effects by comparing adjusted outcomes between treated and untreated units. As an additional check, we further restrict our sample to include only bonds treated between June and December 2016, along with never-treated bonds, thereby minimizing confounding due to treatment timing variation. The resulting estimates remain consistent with our benchmark findings.

To further investigate the role of ESG information in credit risk assessments, we explore two dimensions of heterogeneity: firm-level information asymmetry and exposure to political uncertainty. First, we examine how the effect of ESG integration varies with the degree of information asymmetry across firms. Prior research highlights that credit risk assessments are more challenging when firms disclose less or more opaque information (Duffie and Lando 2001; Yu 2005; Bonsall, Koharki, and Neamtiu 2017; Huang, Svec, and Wu 2021). And information asymmetry is a key determinant of bond pricing and risk premiums in the U.S. corporate bond market (Liao, Chen, and Lu 2009; Wang and Zhang 2009; Benzoni, Garlappi, and Goldstein 2023). We build on these insights by separating our sample into high and low information asymmetry groups based on three distinct proxies. We find that ESG integration by CRAs significantly reduces rating disagreement, and this effect is more pronounced among firms with higher levels of information asymmetry. These results suggest that ESG information serves as a substitute for missing or incomplete financial disclosure, particularly for opaque issuers.

Next, we assess whether the incorporation of ESG information into credit ratings affects firms' borrowing costs. A substantial body of literature has shown that enhanced public disclosure can reduce the cost of debt (e.g., Beatty, Ramesh, and Weber 2002; Armstrong, Guay, and Weber 2010). In particular, more readable and accessible disclosures have been linked to lower credit spreads (Bonsall and Miller 2017). Motivated by this evidence, we test whether ESG integration leads to lower debt costs by improving rating accuracy and reducing uncertainty. Using credit spreads as a proxy, we find that firms with higher ESG disclosure scores experience an average reduction of 4% in credit spreads following ESG incorporation by CRAs. This effect is economically comparable to the liquidity-related pricing differential identified by Chen, Lesmond,

and Wei (2007), who show that a 1 basis point increase in bid-ask spread leads to a 2.29 basis point increase in yield spread (a 3.22% rise).

Finally, we explore whether ESG integration can mitigate credit rating uncertainty in the presence of political risk. Prior research documents that political uncertainty affects risk premiums, asset pricing, and disclosure strategies (Pástor and Veronesi 2012, 2013; Nagar, Schoenfeld, and Wellman 2019; Mekhaimer, Soliman, and Zhang 2024). Firms often respond to higher policy uncertainty with more voluntary disclosure to reduce information asymmetry (Nagar, Schoenfeld, and Wellman 2019). Therefore, we examine whether ESG-based assessments improve credit rating consistency during periods of elevated political risk. Using firm-level political uncertainty scores from Hassan et al. (2019), we find that ESG integration reduces rating disagreement in high-uncertainty settings, particularly where firm disclosures are more complex or less transparent. To test the robustness of this effect, we disaggregate political uncertainty into three categories—Economic Policy & Budget, Environment, and Technology & Infrastructure—and observe consistent reductions in rating disagreement across all dimensions. These results reinforce the view that ESG information enhances the informativeness and reliability of credit assessments, regardless of whether political uncertainty stems from economic or non-economic policy factors.

Our paper contributes to several strands of literature. Firstly, a growing body of literature emphasizes the increasing importance of ESG information and its role in corporate and investment decision-making. Theoretical frameworks suggest ESG factors influence firm behaviour primarily through the non-pecuniary motivations of managers (Pástor, Stambaugh, and Taylor, 2022; Bond and Levit 2025) and investors (Chowdhry, Davies, and Waters 2019; Oehmke and Opp 2025). Conversely, other studies highlight ESG's direct financial impact via risk reduction and improved expected cash flows (Albuquerque, Koskinen, and Zhang 2019; Pedersen, Fitzgibbons, and

Pomorski 2021). Empirically, however, results remain inconclusive: early research shows positive financial effects of superior ESG performance, such as lower capital costs and reduced downside risks (Chava 2014; Flammer 2015; Lins, Servaes, and Tamayo 2017; Hoepner et al. 2024), whereas recent studies question these impacts, citing data limitations, rating inconsistencies, and issues such as greenwashing (Berg, Kölbel, and Rigobon 2022; Christensen, Serafeim, and Sikochi 2022; Baker et al. 2024).

Our paper contributes to this ongoing debate by exploring how sophisticated intermediaries, specifically credit rating agencies (CRAs), integrate ESG information into their assessment processes and their impact on credit rating disagreements. Most existing research focuses on how ESG disclosures influence investor decisions, equity markets, and firm financing (Dhaliwal et al. 2012; Flammer 2013; Duan, Li, and Wen 2025), as well as the real effects of mandatory ESG reporting (Grewal, Riedl, and Serafeim 2019; Gibbons 2024; Krueger et al. 2024). However, there is evidence showing that CRAs are also critical information providers (Akins 2018). Therefore, we examine how credit rating agencies—key information intermediaries in debt markets—process ESG information. Our focus on CRAs expands this literature by evaluating the institutional mechanisms through which non-financial disclosures affect credit risk assessments and borrowing costs.

Finally, our study informs the literature on credit rating disagreement. Prior research documents that ratings can diverge across agencies due to differences in methodology, timing, or access to information (Ederington 1986; Jiang, Stanford, and Xie 2012; Bonsall and Miller 2017; Kronlund 2020). Recent studies attribute these disagreements in part to variation in data quality and availability (Morgan 2002; Akins 2018; Christensen, Serafeim, and Sikochi 2022). We build on this work by analysing the role of ESG information, characterized by heterogeneity and

measurement challenges, in shaping rating divergence. Using a difference-in-differences design around a quasi-natural experiment, we provide causal evidence on how the structured integration of ESG data by CRAs reduces uncertainty and enhances rating consistency.

The remainder of this paper is structured as follows: Section 2 reviews the institutional background and hypothesis development; Section 3 presents the data and summary statistics; Section 4 reports the empirical results, followed by robustness tests and policy uncertainty analyses; and Section 7 concludes the paper.

2. Institutional background and Hypothesis Development

2.1 ESG in Credit Risk and Ratings initiative

In 2016, the UN-supported Principles for Responsible Investment (PRI) launched the ESG in *Credit Risk and Ratings Statement*⁷, a formal initiative aimed at encouraging credit rating agencies (CRAs) to systematically and transparently integrate ESG factors into creditworthiness assessments. The initiative seeks to address both systemic and idiosyncratic risks through enhanced ESG consideration in rating methodologies. To ensure accountability and monitor implementation, the PRI requires participating CRAs to submit quarterly updates on their progress and practices⁸.

⁷ This statement is supported by around 180 investors with over \$40 trillion of assets under management, and 25 CRAs until 2022 (PRI, 2023).

⁸ Detailed quarterly updates on how Credit Rating Agencies (CRAs) are integrating ESG factors into creditworthiness assessments can be found on the UNPRI website: <https://www.unpri.org/credit-risk-and-ratings/credit-rating-agency-cra-quarterly-updates/5631.article>.

Leading CRAs signed the PRI Statement at different times: Moody’s Investors Service and S&P Global Ratings signed in May 2016, while Fitch Ratings followed in August 2018 (PRI, 2023). Figure. 1 illustrates the adoption timeline for these agencies.

Insert Figure. 1

We treat the signing of the PRI Statement as a quasi-natural experiment signalling the CRA’s public commitment to ESG integration. This commitment is presumed to influence the structure and transparency of credit risk assessments. Our empirical analysis spans May 2013 to August 2018, a period that includes the pre- and post-ESG incorporation regimes for Moody’s but not Fitch. This staggered adoption allows us to isolate the effects of ESG integration by comparing Moody’s with Fitch, which did not sign the PRI Statement during the sample period.

Importantly, ESG disclosure was not mandatory in the U.S. during this time (Krueger et al. 2024), giving firms substantial discretion over both the quantity and quality of ESG information they disclose. This variation affects the extent to which CRAs can incorporate ESG information in practice, making the U.S. credit market a particularly suitable setting for empirical analysis.

To test whether ESG considerations shape credit ratings, we exploit cross-sectional variation in firms’ ESG transparency. We proxy transparency with ESG disclosure scores—composite measures of the volume of ESG-related information firms publish (Baldini et al. 2018; Li et al. 2018; Christensen, Hail, and Leuz 2021). Higher scores imply a richer ESG information set available to credit-rating agencies; if this information is value-relevant, greater transparency should yield more precise credit assessments and narrower credit rating dispersion after CRAs incorporate ESG information in their rating methodologies.

2.2 Hypothesis development

Credit rating agencies (CRAs) provide independent analytical judgments in the form of credit ratings, which are designed to capture longer-term or “persistent” changes in credit risk. Their effectiveness in doing so depends heavily on both their privileged access to private information and their ability to process that information efficiently (Gredil et al. 2022). Within this framework, environmental, social, and governance (ESG) information may represent a valuable informational complement: by illuminating firms’ exposures to non-financial risks, it has the potential to strengthen evaluations of long-term performance and resilience (e.g., Lins, Servaes, and Tamayo 2017). When systematically embedded into rating methodologies, ESG factors could thereby enhance the accuracy and consistency of credit quality assessments across agencies, reducing the extent of rating disagreement.

At the same time, the integration of ESG information introduces an important complication. The information-processing literature demonstrates that different market participants frequently interpret identical information in divergent ways, giving rise to price fluctuations and trading dynamics (e.g., Kandel and Pearson 1995; Banerjee and Kremer 2010; Banerjee 2011). ESG disclosures, in particular, are non-financial, frequently broad in scope, and predominantly qualitative, which leaves ample room for subjective interpretation (Banerjee et al., 2020). As a result, the integration of ESG considerations into credit risk assessments is highly likely to induce CRAs to arrive at distinct interpretations, thereby producing divergent judgments of creditworthiness. This heterogeneity underscores the inherent ambiguity regarding whether ESG integration serves to attenuate or, conversely, to exacerbate rating disagreements.

Building on this reasoning, we hypothesize that ESG integration by CRAs reduces rating disagreement by mitigating information asymmetry. This hypothesis is motivated by three economic mechanisms.

First, ESG disclosure contains value-relevant information. Prior literature shows that greater disclosure improves the informational environment by facilitating investor understanding of firm risks and future cash flows (Easley and O'hara 2004). ESG disclosure, in particular, provides insights into how firms manage stakeholder relationships, environmental exposures, and governance structures, all of which may influence creditworthiness (Starks 2023). Better disclosure also invites external monitoring by analysts and institutional investors, thereby enhancing transparency (Bushman and Smith 2001). Moreover, ESG disclosure can generate learning externalities, as firms benchmark their practices against peers (Admati and Pfleiderer 2000). Overall, improved information quality should reduce disagreement among CRAs evaluating the same entity.

Second, ESG factors are economically meaningful in the context of credit risk. Prior studies document that ESG engagement reduces downside risk exposure (Hoepner et al. 2024). Climate risk, a component of environmental disclosure, is priced in derivative markets (Ilhan, Sautner, and Vilkov 2021) and in bond spreads (Dickerson, Mueller, and Robotti 2023). To the extent that ESG factors capture latent risk channels, integrating them into credit analysis should align rating assessments more closely across agencies.

Third, CRAs possess the analytical capacity to process non-financial information. Historically, CRAs have incorporated both qualitative and quantitative data in their models, drawing from diverse sources beyond traditional financial statements (Roychowdhury and Srinivasan 2019). As

such, CRAs are well-positioned to evaluate ESG disclosures and convert them into risk-relevant inputs for credit assessments. Thus, when ESG information is systematically incorporated, it should help harmonize ratings across agencies by reducing interpretive ambiguity.

These considerations lead to our central hypothesis:

H1: *Ceteris paribus*, greater firm ESG disclosure is associated with lower credit rating disagreement between CRAs.

We test this hypothesis using a difference-in-differences design that exploits the staggered timing of PRI Statement adoption across CRAs, combined with cross-sectional variation in firm ESG transparency.

3. Data and summary statistics

3.1 Data sources

We obtain our corporate bond sample between 2013 and 2018 in the Mergent Fixed Income Securities Database (FISD). First, we use the database identifiers, BOND CUSIP (Committee on Uniform Security Identification Procedures), to match the Moody's and Fitch rating for the same bond at the same month. Then, we link the rating dataset to bond-specific control variables by identifying the BOND CUSIP. After constructing the bond dataset, we merge it with financial ratios extracted from Compustat by matching GVKEY (Global Company Key) and CRSP PERMCO. Additionally, the ESG disclosure data capturing the extent of firms' ESG disclosure is sourced from Bloomberg. Then, we use the ISSUER CUSIP as identifier to combine the ESG disclosure data with the abovementioned dataset. To further identify the degree of firms' information asymmetry, we collect analyst earnings forecast data to construct measures of

asymmetric information. Finally, we link the constructed dataset with the Institutional Broker's Estimate System (IBES) database by ISSUER CUSIP. Following commonly used selection criteria in the literature; we exclude companies that do not have complete records on our variables.

3.2 Ratings

The original rating letters from Moody's and Fitch are converted to numbers, with higher numbers indicating worse credit ratings. Table 1 reports the conversion of Moody's and Fitch letter credit ratings to numeric ratings, as well as the distribution of bond ratings during our sample period (May 2013 to August 2018). It can be observed that about 80% of corporate bonds are assigned from Baa3 to A1 for Moody's and from BBB- to A+ for Fitch. We follow prior empirical research on the rating disagreements (Morgan 2002; Bonsall and Miller 2017; Akins 2018; Christensen, Serafeim, and Sikochi 2022) to construct our measure of bond rating disagreement, the absolute value of the difference between the numerical value of categorical ratings assigned to the same bond issued from Moody's and Fitch, $rating\ disagreement = |Moody's - Fitch|$. In addition, we define two indicator variables: *Overrated* and *Underrated*. The variable *Overrated* equals 1 if the rating value assigned by Moody's is higher than that assigned by Fitch for the same bond, and 0 otherwise. Conversely, *Underrated* equals 1 if the rating value assigned by Moody's is lower than that assigned by Fitch for the same bond, and 0 otherwise

Insert Table 1

3.3 The ESG disclosure data

Our study explores the relationship between the integration of ESG information in credit rating assessments and bond rating disagreements. To this end, we employ a quasi-natural experiment,

assigning bonds to the treatment based on the extent of the corresponding ESG disclosure amount (as opposed to the quality of the ESG data) and the timing of their ratings. Following previous research (Baldini et al. 2018; Li et al. 2018; Christensen, Hail, and Leuz 2021), we use the ESG disclosure scores to measure the amount of ESG information that a company publishes across various sources accessible by Bloomberg. Companies that do not disclose any ESG information receive a score of 0. The score ranges from 0.1 for companies that disclose a minimal amount of ESG data to 100 for those that disclose every data point collected by Bloomberg. It should be noted that this score does not measure the company's ESG information quality. In our study, we identify bond issuers with a higher ESG disclosure score, indicating that the bond issuer provides more comprehensive ESG information. Consequently, the more ESG information a bond issuer discloses, the more likely it is that CRAs can incorporate more ESG information into their credit rating models. This implies that the impact of integrating ESG information into credit risk analysis will vary between bonds issued by firms with higher ESG disclosure scores and those with lower ESG disclosure scores.

3.4 Control variables

Given our interest in the influence of ESG incorporation in the credit rating process on bond rating disagreements, we select control variables related to bond issuers and bond characteristics, guided by existing empirical literature (e.g., Morgan 2002; Livingston, Naranjo, and Zhou 2007; Jiang, Stanford, and Xie 2012; Kedia, Rajgopal, and Zhou 2014; Bonsall and Miller 2017; Akins 2018). For bond issuer-level controls, we apply firm size (AT), the ratio of tangible assets (TA), profitability (PRO), market-to-book ratio (MB) and leverage (LEV) to measure the financial health of the corresponding bond issuer. To control for the potential influence of outliers, we winsorize all control variables at the 1st and 99th percentiles. For bond-specific controls, we employ the

outstanding amount (AM), the remaining maturity years (MAT), an indicator variable to identify the callable bond (CALL), a puttable bond dummy (PUT), and medium-term note dummy (MTN) to capture the bond characteristics. The detailed definition of these variables is listed in the Appendix Table A.1.

3.5 Summary statistics

Our final sample includes 7012 bonds issued by 557 companies, of which more than 80% are investment grade. Table 2 shows descriptive statistics for the 233,405 observations used in our model. The average bond issuance is for \$210.26 million, with a maturity of 13.83 years. Untabulated analyses reveal that the average ratings assigned by the two agencies differ statistically significantly each year, with approximately 60% of bonds in our sample receiving differing ratings from the agencies. We use the industry-specific median ESG disclosure score as a threshold to divide the dataset into two groups. Bonds with ESG disclosure scores below the industry median are classified as low ESG disclosure, while those with scores equal to or above the median are categorized as high ESG disclosure in the given year. Table 3 examines the equality of means in absolute rating disagreements across bonds with varying levels of ESG disclosure by year. The results in Column (6) demonstrate a statistically significant difference in rating disagreements between bonds with low and high ESG disclosure scores. Furthermore, the findings reveal a distinct shift in the trend of absolute rating disagreements before and after 2016, providing empirical evidence to support the hypothesis that incorporating ESG information into the credit rating process is related to the change of rating disagreements. This conclusion is further supported by Figure 2, which illustrates a distinct shift in the trend of average absolute rating divergence between bond ratings assessed with ESG integration and those without ESG integration during the period 2016-2017.

Figure 2 plots the trend in absolute rating disagreements between Moody's and Fitch Ratings for bond issuers with high versus low ESG disclosure from 2013 to 2018, with the vertical red line marking the timing of Moody's signing the PRI ESG Statement. Prior to 2016, rating disagreements for high- and low-disclosure issuers followed largely parallel paths. The crossover observed from 2016 to 2017—shaded in Figure 2—together with the subsequent post-2017 dynamics suggests a structural shift in the relationship. As the crossover period coincides with Moody's signing the PRI ESG Statement, the evidence indicates that the event reduced rating uncertainty for firms with greater ESG transparency while amplifying it for firms with limited disclosure. These results are consistent with our main hypothesis that ESG integration into the credit rating process enhances rating consensus among CRAs.

Insert Table 2

Insert Table 3

Insert Figure. 2

To further investigate whether the observed shift is related to the timing of credit rating agencies' (CRAs) announcements regarding the transparent and systematic incorporation of ESG information into credit ratings, and to better gauge our research framework, we use May 2016—when Moody's Investors Service signed the ESG in Credit Risk and Ratings Statement—as the cutoff point to divide the full sample into pre-ESG incorporation and post-ESG incorporation periods. This approach generates four distinct groups: firms with lower ESG disclosures prior to ESG incorporation, firms with lower ESG disclosures following ESG incorporation, firms with higher ESG disclosures prior to ESG incorporation, and firms with higher ESG disclosures post-ESG incorporation. In Table 4, we report the p-values for tests of equality of means of rating

disagreements across these groups. As expected, the mean values of absolute rating disagreements are statistically significantly different between low and high ESG disclosure groups within the pre- and post-ESG incorporation periods. These results indicate a correlation between rating disagreements and the application of ESG factors in credit risk analysis.

Insert Table 4

4. Empirical results

4.1 Main results

To examine whether the transparent and systematic incorporation of ESG into credit rating analysis contributes to a reduction in rating disagreement among CRAs, we estimate the following model, controlling for issuer- and bond-specific characteristics commonly used in prior research to explain rating disagreements (Morgan 2002; Campbell and Taksler 2003; Jiang, Stanford, and Xie 2012; Bonsall and Miller 2017; Akins 2018; Badoer, Demiroglu, and James 2019; Christensen, Serafeim, and Sikochi 2022):

$$rating\ disagreement_{i,t} = \beta_0 + \beta_1 ESG\ integration_{i,t} + \beta_i \sum Controls_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t}, \quad (1)$$

where $rating\ disagreement_{i,t}$ is the rating disagreement of a bond i at month t between Moody's and Fitch, $ESG\ integration_{i,t}$ is an indicator variable that takes the value of one if a bond i is rated at month t after May 2016, and the corresponding ESG disclosure score exceeds the industry median in that year, and zero otherwise; $Controls_{i,t}$ are issuer-level and bond-level variables in the previous studies, which are listed in the Appendix Table A.1, α_i and τ_t are firm fixed effects and month fixed effects to identify within-firm variation the and adjust for time trends. If, as proposed in H1, transparent and systematically incorporation of ESG factor in credit risk

analysis reduce the information asymmetry and opacity, we predict the estimated coefficient of *ESG integration*_{*i,t*} in equation (1) to be statistically significantly negative.

Table 5 presents the estimated effect of credit rating agencies transparently and systematically using ESG information during credit rating process on bond rating disagreements in equation (1), (2) and (3). Columns (1) and (2) presents the results of estimating model (1) with and without control variables at the issuer- and bond-level, where dependent variable is *rating disagreement* defined as the absolute value of the difference between the numerical value of categorical ratings assigned to the same bond issued from Moody's and Fitch. The estimated coefficients of *ESG integration* are statistically significant and negative at 1% level in both Columns (1) and (2). Specifically, in Column (1), rating disagreement decreases by 5% following Moody's signing of the PRI ESG statement. In Column (2), the rating disagreement declines by 7% after Moody's adoption of the PRI ESG statement, accounting for various characteristics of the CRAs. These results suggest that rating disagreements between Fitch and Moody's are reduced subsequent to Moody's signing the PRI ESG statement.

While the model (1) captures the magnitude of rating disagreement between CRAs, we further investigate whether CRAs transparently and systematically applying ESG information into credit rating process can affect the probability of Moody's issuing higher/lower rating value level than Fitch for the same bond. Thus, we define a dummy as 1, overrated if the rating value of Moody's is larger than Fitch for the same bond, and otherwise 0. And we also employ underrated a dummy, which equals to 1, if the rating value of Moody's is smaller than Fitch for the same bond, and otherwise 0. The equation (1) is modified into the following:

$$overrated_{i,t} = \beta_0 + \beta_1 ESG\ integration_{i,t} + \beta_i \sum Controls_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t}, \quad (2)$$

and

$$underrated_{i,t} = \beta_0 + \beta_1 ESG\ integration_{i,t} + \beta_i \sum Controls_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t}, \quad (3)$$

where $overrated_{i,t}$ is the indicator that a bond i at month t receives a rating value from Moody's is larger than Fitch, $underrated_{i,t}$ is the indicator that a bond i at month t receives a rating value from Moody's is smaller than Fitch and other variables are the same meaning in equation (1).

The estimated coefficients of *ESG integration* in model (2) and (3) are presented in Columns (3) to (6) of Table 5, aligning with the results reported in Columns (1) and (2). In Column (3), Moody's signing of the PRI ESG Statement is associated with approximately a 1% decrease in the magnitude of the overrated variable. This reduction increases to around 2% after accounting for different characteristics of credit rating agencies (CRAs) in Column (4). A similar trend is observed in Columns (5) and (6). In conclusion, the negative and statistically significant *ESG integration* estimates in Columns (3) through (6) provide evidence that the transparent and systematic application of ESG information reduces the likelihood of Moody's assigning a bond a lower or higher rating compared to Fitch.

Overall, the results in Table 5 support that the explicit, transparent and systematic use of ESG information in credit rating analysis can reduce rating disagreements between CRAs and improve information transparency of corporate bonds. To capture the discrete feature of dependent variables, we re-estimate models (1), (2) and (3) by using ordered logit and logit models respectively and present the results in Table 6. All results are consistent with our main results in Table 5. Since including multiple fixed effects can lead to biased coefficient estimates in logit models (Chamberlain 1980), the results in Table 6 are applied as our robustness tests.

Insert Table 5

Insert Table 6

4.2 Information asymmetry

Information asymmetry has been shown to significantly influence both risk assessments and yield premiums in the U.S. corporate bond market (see, for instance, Liao, Chen, and Lu 2009; Wang and Zhang 2009; Lu, Chen, and Liao 2010). When market participants lack access to reliable or complete information, it becomes more difficult to evaluate a firm's creditworthiness accurately. Consequently, firms characterized by higher levels of information asymmetry pose greater challenges for accurately assessing their creditworthiness (Huang, Svec, and Wu 2021). This provides an opportunity to investigate whether the transparent and systematic integration of ESG metrics into the credit rating process can better capture an entity's creditworthiness by addressing information gaps, reducing corporate information asymmetry, and subsequently enhancing credit risk market transparency. Such an approach could also help mitigate rating disagreements among credit rating agencies. To explore this, we segment our sample into subsamples based on the degree of information asymmetry associated with each firm and re-estimate models (1), (2) and (3).

To proxy the information asymmetry of a firm, we apply three measures following previous research (see for instance, Krishnaswami and Subramaniam 1999; Duchin, Matsusaka, and Ozbas 2010; Leary and Roberts 2010). We use the median number of industry analysts as a first proxy index to divide the full sample into two groups: firms with higher analyst coverage and those with lower analyst coverage. The second measure involves the dispersion of analyst forecasts for a firm, which is quantified as the standard deviation of earnings forecasts across analysts, normalized by the firm's total book assets for a given year. Firms with forecast dispersion higher than the industry

median are categorized into the high-dispersion sample, while those below the median are placed into the low-dispersion sample. Finally, we utilize the industry median of analyst forecast errors to classify firms based on the magnitude of forecast errors. The forecast error is calculated as the absolute difference between the mean analyst earnings forecast and the actual earnings, normalized by the firm's total book assets for a given year. Firms with forecast errors larger than the industry median are placed in the large-forecast-error sample, and those with smaller errors in the small-forecast-error sample.

Existing literature suggests that when a firm is followed by a relatively small number of analysts, the limited external coverage increases information opacity, making it more difficult for market participants to assess the firm's financial health accurately. Additionally, high earnings forecast dispersion among analysts or substantial forecast errors signal a lack of consensus regarding the firm's performance, which further exacerbates information asymmetry. These discrepancies in analyst assessments indicate elevated levels of uncertainty about the firm's true creditworthiness. In this context, we hypothesize that the transparent and systematic integration of ESG factors into the credit rating process by credit rating agencies (CRAs) could help capture additional pertinent information, thereby reducing the information gaps that lead to rating disagreements. This approach would enhance transparency in the credit rating market and help mitigate discrepancies in ratings across CRAs.

Table 7 reports OLS estimations of Model (1) in three sets of subsamples. These results provide several insights. First, results in firm sample followed by few analysts presented in column (2) in line with our benchmark effect of transparently and systematically incorporating ESG factors into credit rating analysis, the estimated coefficient of *ESG integration* is approximately -8%, which is statistically significant and negative at 5% level. However, the estimated coefficient of

ESG integration in column (1) for firm sample with more analysts is not statistically significant. This suggests that the impact of incorporating ESG considerations into the credit rating process on bond rating divergences is statistically more significant for bond issuers with higher levels of information asymmetry, compared to those with lower information asymmetry. Moving to columns (3) to (6), in the high/low earning forecast dispersion and large/small earning forecast errors subsample, the estimated coefficient of *ESG integration* is only statistically significant and negative at 1% level in high earning forecast dispersion and large forecast errors subsamples. All evidence in Table 7 suggests that for companies with greater information asymmetry, transparently and systematically incorporating ESG information into credit rating analysis serves as a more effective approach to enhancing information transparency in the credit risk market and reducing rating disagreements across CRAs.

The OLS estimations of Model (2) and (3) in three sets of subsamples are listed in Table 8. The similar findings can be detected from Columns (1) to (6) in both panel A and B. Incorporating ESG in CRA leads to decrease in the *overrated/underrated* variable and suggests that transparently and systematically employing ESG information can reduce the probability that Moody's assigns a bond in a lower/higher rating than Fitch — particularly for firms with high information asymmetry. It supports our benchmark results.

Insert Table 7

Insert Table 8

4.3 Parallel-trends tests

Our results suggest transparently and systematically using ESG information in credit rating process can reduce bond rating disagreements between CRAs. To verify the validity of our results, we start the evaluation of the parallel trends assumption. Figure. 2 is a graphical analysis showing the trend of average absolute rating disagreement around the signing of the ESG statement, which evidence that the rating disagreement tendency changes.

To minimize potential confounding arising from variation in treatment timing, we restrict the sample to bonds affected by ESG integration between June and December 2016, along with a control group of never-treated bonds. We then assess the validity of the parallel-trends assumption. Figure. 3 presents supporting evidence, where the dashed lines in each figure indicating the 95% confidence intervals adjusted for bond-level clustering. The results demonstrate a statistically significant decrease in rating disagreements for the two years following Moody's signing of the PRI ESG statement. Overall, there is no evidence of a substantial violation of the parallel-trends assumption prior to the treatment period. The estimated coefficients reported in Figure 3 are derived from the following regression model:

$$\begin{aligned}
 \text{rating disagreement}_{i,t} &= \beta_0 + \beta_1 \text{ESG integration}^{-3} + \beta_2 \text{ESG integration}^{-2} + \beta_3 \text{ESG integration}^{+1} + \beta_4 \text{ESG integration}^{+2} \\
 &+ \beta_5 \text{ESG integration}^{+3} + \beta_i \sum \text{Controls}_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t},
 \end{aligned} \tag{4}$$

where the $\text{ESG integration}^{-3}$ equals one if a bond is rated three years prior to the integration of ESG information into the credit rating process, and zero otherwise. Similarly, $\text{ESG integration}^{-2}$ equals one if a bond is rated two years before ESG integration, and zero otherwise. In contrast, $\text{ESG integration}^{+1}$, $\text{ESG integration}^{+2}$ and $\text{ESG integration}^{+3}$ equal one if a bond is rated one year, two years and three years after the ESG integration in the rating assessment. equal one

if a bond is rated one, two, and three years after ESG integration, respectively. Bonds rated one year prior to ESG integration are excluded from the analysis and serve as the reference group. This setup allows us to estimate the dynamic effect of ESG integration on rating disagreements relative to the year immediately preceding Moody's adoption of ESG factors in its rating assessment.

Insert Figure. 3

Figure 3 also reveals an important dynamic: the effect of ESG integration into credit rating assessments becomes statistically insignificant approximately three years after Moody's began incorporating ESG factors into its rating methodology. While this finding may appear to diverge from our benchmark results, it is in fact consistent with broader trends in the credit rating industry. According to PRI (2023), Fitch signed the PRI ESG Statement in August 2018, signalling its commitment to embedding ESG considerations into its own credit rating framework. Given the limited time horizon of our empirical setting, observations near the end of the sample period likely overlap with the phase in which Fitch began integrating ESG into its assessments. Consequently, the marginal impact of Moody's ESG incorporation on rating disagreements between Moody's and Fitch diminishes over time. This observed attenuation supports the internal validity of our empirical strategy and aligns with contemporaneous shifts in rating agency practices.

4.4 Cost of debt

The findings related to rating disagreements suggest that incorporating Environmental, Social, and Governance (ESG) factors into the credit rating process can effectively reduce rating divergence between credit rating agencies (CRAs), thereby enhancing transparency and reduce uncertainty in the credit risk market. This increased transparency in credit ratings may, in turn, influence the broader financial market, particularly in terms of the cost of borrowing. In light of this, we now

turn our attention to examining the potential impact of integrating ESG information into credit rating analysis on the cost of debt for firms in the financial market.

To assess this effect, we modify the quasi-experimental design based on the event of Moody's signing the PRI ESG in Credit Rating Statement. This event serves as an exogenous shock that allows us to explore whether the transparent and systematic incorporation of ESG information into the credit rating process affects the issue-level credit spreads of corporate bonds. We hypothesize that the availability of more comprehensive ESG disclosures enables rating agencies to better assess the ESG-related risks and opportunities associated with a firm, which could lead to more accurate credit risk assessments.

By examining how the transparent incorporation of ESG factors influences bond yields, we aim to provide insight into the broader implications of ESG integration for corporate financing costs. Existing literature suggests that the yield on corporate bonds is influenced by several factors, including credit risk, liquidity, bond-specific characteristics, interest rates, and stock market volatility (e.g., Longstaff and Schwartz 1995; Duffee 1998; Collin-Dufresne, Goldstein, and Martin 2001; Elton et al. 2001; Campbell and Taksler 2003; Longstaff, Mithal, and Neis 2005; Helwege, Huang, and Wang 2014). Given these determinants, the model used to estimate the cost of debt incorporates these factors to isolate the effect of ESG disclosure on credit spreads:

$$credit\ spread_{i,t} = \beta_0 + \beta_1 ESG\ integration_{i,t} + \beta_i \sum Controls_CS_{i,t-1} + \eta_i + \theta_t + \varepsilon_{i,t}, \quad (5)$$

where $credit\ spread_{i,t}$ is the logarithm of the difference between the yield of the benchmark treasury issue and the issue's offering yield of a bond i at year t expressed in basis points measuring the cost of debt and $ESG\ integration_{i,t}$ is a dummy variable that is 1 if a bond i is

rated year t after May 2016 and the corresponding last fiscal year-end ESG disclosure score exceeds the industry median in that year, and zero otherwise; $Controls_{cs_{i,t-1}}$ is observed in the last fiscal year-end before the announcement date of bond i and constructed by all control variables in equation (1) and return on assets (ROA), interest coverage (INTCOV), VIX, term spread (T10Y2Y), and 10-year Benchmark Treasury rates (DGS10)⁹, η_i and θ_t are firm fixed effects and year fixed effects.

The results presented in Table 9 indicate that the estimated influence of CRAs transparently and systematically applying ESG information during credit rating analysis on the cost of debt in equation (5). The estimated coefficients of *ESG integration* are statistically significant and negative with or without controls. In Column 2, the credit spread reduces by 4% after Moody's signing PRI ESG statement controlling other variables. These findings reinforce our primary results and offer compelling evidence that integrating ESG information into credit rating analysis improves information transparency, which, in turn, leads to a reduction in the cost of debt for firms.

Insert Table 9

5. Robustness tests

Since our dataset related to bond-level ratings, we first re-estimate our benchmark model by OLS and logit models controlling bond fixed effects and results are reported in Appendix B, Table B.1. We find that the significance levels and negative values are unaffected by the inclusion of bond fixed effects in the model (1), (2) and (3). Although the estimated results of *ESG integration* in columns (3) and (4) of Appendix B, Table B.1 are not statistically significant, the results are still

⁹ The detailed explanation of variables is listed in table A.1 in Appendix A.

negative. Following our benchmark, we re-estimate the above model by logit models considering the discrete feature of dependent variables. The results are provided in Appendix B, Table B.2, which is consistent with our main results.

Second, according to the PRI (2023) report, another major credit rating agency, S&P Global Ratings, also signed the statement in May 2016, committing to the transparent and systematic incorporation of ESG factors into its credit rating analysis. This provides an opportunity to further support our main conclusions. We calculated the rating disagreements between S&P Global Ratings and Fitch Group and incorporated them into both models (1) as robustness tests. The OLS estimates for the ESG integration variable, reported in Columns (1) and (2) of Appendix B, Table B.3, are approximately -8% , aligning closely with the magnitude of our benchmark results. We subsequently re-estimated the models using a logit specification, with the results presented in Columns (3) and (4) of the same table. Additionally, we replaced firm fixed effects with bond fixed effects in the benchmark model. The corresponding results are shown in Columns (5) through (8). Across all specifications, the estimated coefficients remain consistent in sign and magnitude. These findings reinforce our main conclusion that the transparent and systematic incorporation of ESG information into credit rating analysis reduces rating disagreements between credit rating agencies.

Moreover, in our study, ESG integration into the bond rating process occurs at different times across bonds, resulting in staggered treatment adoption. This staggered implementation can introduce bias into treatment effect estimates when using ordinary least squares (OLS) within a conventional difference-in-differences (DiD) framework (Borusyak, Jaravel, and Spiess 2024). To address treatment effect heterogeneity and variation in treatment timing, we adopt a more robust and efficient estimator—specifically, the two-stage difference-in-differences (2SDD) estimator

proposed by Gardner et al. (2025)¹⁰. This approach extends the imputation framework of Borusyak, Jaravel, and Spiess (2024) and conducts inference under a standard generalized method of moments (GMM) asymptotic framework. It estimates treatment effects by comparing treated and untreated potential outcomes after removing group and period fixed effects—identified solely from untreated observations—thereby producing consistent estimates in the presence of heterogeneous and staggered treatments.

We report the average treatment effect on the treated (ATT), both with and without control variables, using the 2SDD estimator in our benchmark models (Panel A, Appendix B, Table B.4). Across all model specifications, the estimated coefficients remain significantly negative and are closely aligned in magnitude with the benchmark estimates presented in Table 5, even when control variables are included.

As an additional robustness check to reduce treatment effect heterogeneity and variation in treatment timing, we further restrict the sample to include only treated bonds observed between June and December 2016, along with never-treated bonds. The resulting estimates, reported in Panel B of Appendix B, Table B.4, align with our main findings, thereby reinforcing the robustness of our results.

6. Policy uncertainty

As an increasing trend of temporary or provisional laws issued in US, companies are facing increasing uncertainty in the political environment (Nagar, Schoenfeld, and Wellman 2019). This

¹⁰ Compared to alternative methods such as those developed by de Chaisemartin and d'Haultfoeuille (2020) and Callaway and Sant'Anna (2021), the 2SDD estimator offers computational efficiency and ease of implementation, requiring only minimal additional coding beyond standard regression procedures.

has prompted a growing literature studying the uncertainty of the political system and its impact on the firms' behaviour (see for instance, Julio and Yook 2012; Brogaard and Detzel 2015; Bonaime, Gulen, and Ion 2018; Hassan et al. 2019; Nagar, Schoenfeld, and Wellman 2019; and Peng, Colak, and Shen 2023). Nagar, Schoenfeld, and Wellman (2019) confirm that firms facing greater political uncertainty experience higher levels of information asymmetry among investors of the firm, prompting managers to respond with more voluntary disclosures. As the increase of information disclosure due to policy risks, this provides us with an opportunity to explore how incorporating ESG into the credit rating process affects the information transparency of credit ratings under varying levels of policy uncertainty. In this part, we use the firm-level political risk defined by Hassan et al. (2019), which measures each firm's risk to a change in government policy. Thus, the benchmark model (1) is modified by applying interaction terms between *ESG integration* and a proxy of firm-level political risk, *PRISK*:

*rating disagreement*_{*i,t*}

$$= \beta_0 + \beta_1 ESG\ integration_{i,t} * PRISK_{i,t} + \beta_2 ESG\ integration_{i,t} + \beta_3 PRISK_{i,t} + \beta_i \sum Controls + \alpha_i + \tau_t + \varepsilon_{i,t}, \quad (6)$$

where *PRISK*_{*i,t*} is the firm-level political risk variable extracted from textual analysis of quarterly earnings conference-call transcripts (Hassan et al. 2019) for bond *i* at month *t*. As the before, we follow equation (1) and use the same controls in equation (6).

If corporate managers disclose more information to alleviate information asymmetry caused by policy risks, incorporating ESG information into the rating process to conduct a more comprehensive assessment of corporate behaviour could enhance transparency in the credit rating market, reduce information opacity, and help narrow rating disagreements between CRAs. Thus,

we expect that the coefficient of $ESG\ integration_{i,t} * PRISK_{i,t}$ is negative. As we all know, there exist different political topics among political risk. We tend to further investigate the impact of incorporating ESG information into credit risk analysis on rating disagreements when companies face different types of political risks. We thus apply three difference proxies measuring three types of political risks faced by firms, $PRISK_ECO$, $PRISK_ENV$ and $PRISK_TEC$ to replace $PRISK$ in equation (6) to detect how applying ESG information into credit rating process influence the bond rating disagreements conditional on different type of political risk. The $PRISK_ECO_{i,t}$, $PRISK_ENV_{i,t}$ and $PRISK_TEC_{i,t}$ assess the Economic Policy & Budget, Environment and Technology & Infrastructure political risk of the corresponding bond issuer for a bond i at month t respectively (Hassan et al. 2019).

Table 10 presents the estimation related to equations (6). In Column (1) to Column (8) the estimated coefficients are all statistically significant negative and the magnitude of both estimates is similar. In Column (2), the estimate for the interaction term, $ESG\ integration_{i,t} * PRISK_{i,t}$ suggests a one-standard- deviation increase in the firm-level political risk causes a 0.0204 decrease¹¹ in rating disagreements relative to the average. Overall, our findings suggest that incorporating ESG information into rating analysis can reduce rating disagreements for firms facing higher levels of firm-specific political risk, regardless of the type of political risk. This highlights that integrating ESG factors into the credit rating process is an effective approach to enhancing credit rating transparency, particularly for firms exposed to significant political uncertainties.

¹¹ The standard deviation of $PRISK$ is 203.9358.

7. Conclusion

As the importance of ESG activities for corporate sustainability continues to gain recognition, global investors and other market participants are increasingly emphasizing the non-financial ESG information disclosed by companies. Understanding the impact of this ESG information on financial markets has become a central focus of research. In this paper, we provide empirical evidence that integrating ESG disclosures into the credit rating process enhances consistency among credit rating agencies (CRAs).

Using a monthly corporate bonds dataset and employing a difference-in-differences (DiD) model, we investigate how the transparent and systematic incorporation of ESG factors into credit risk analysis affects uncertainty in credit rating quality. First, our results show that incorporating ESG information into the credit rating process reduces rating disagreements and lowers the likelihood of Moody's assigning a higher or lower rating relative to Fitch. Second, when accounting for varying levels of information asymmetry among firms, our findings suggest that the integration of ESG information has a stronger impact on reducing rating disagreements for firms with higher levels of information asymmetry. Additionally, we analyse the impact of ESG integration on the cost of debt and find that incorporating ESG factors into credit ratings is associated with a reduction in borrowing costs. Moreover, ESG integration continues to mitigate bond rating disagreements, particularly for firms operating in politically uncertain environments.

Overall, our findings indicate that incorporating ESG information into the credit rating process enhances consistency among CRAs and improves transparency in the credit market. This study provides a unique opportunity to assess the role of ESG factors in financial markets by leveraging

the quasi-natural experiment of CRAs adopting ESG considerations in their rating methodologies. The results highlight the critical importance of ESG integration in fostering sustainable and transparent financial systems, offering valuable insights for policymakers, investors, and rating agencies.

Despite the robustness of our findings, several avenues for future research remain open. Future studies could develop more direct measures of ESG information, explore the long-term effects of ESG integration on market stability, or examine cross-country differences in the adoption and application of ESG factors.

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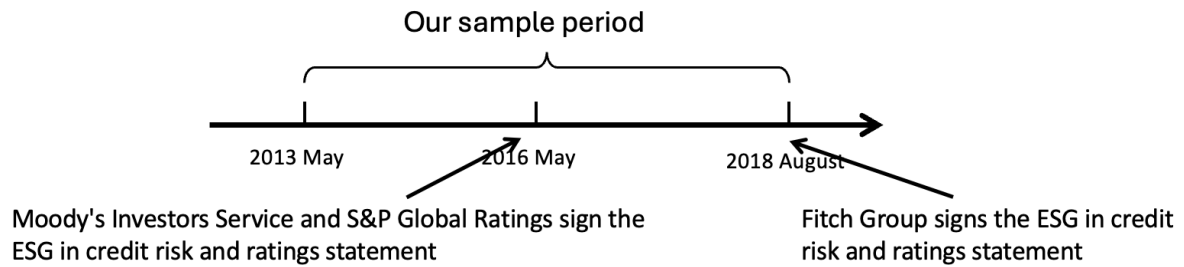


Figure. 1 Timeline of Signing the PRI ESG Statement. This figure presents the chronological timeline indicating when the three major credit rating agencies—Moody’s, S&P Global Ratings, and Fitch Ratings—signed the “ESG in Credit Risk and Ratings Statement.” The data are sourced from the Principles for Responsible Investment (PRI, 2023).

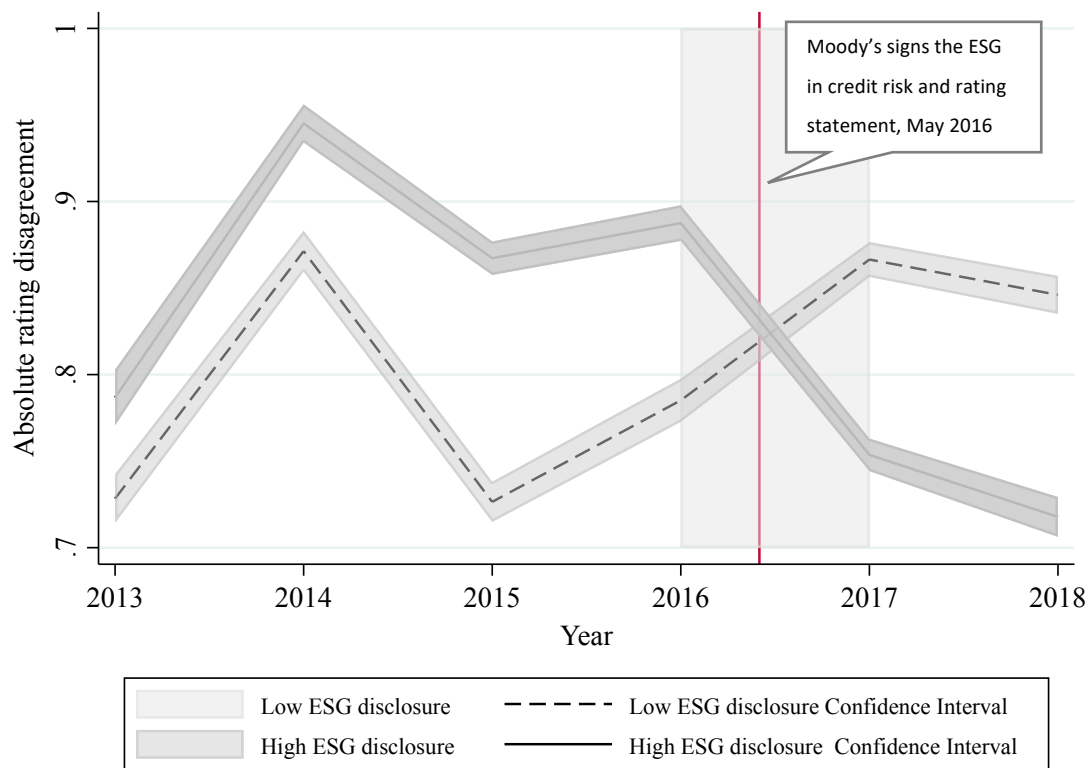


Figure 2. Mean Value Plot of Absolute Rating Disagreements Between Moody's and Fitch Ratings by month. This figure displays the monthly mean absolute rating disagreements between Moody's and Fitch for the same bonds. The dashed line denotes the mean absolute disagreement for bonds issued by firms with ESG disclosure scores below the industry median in a given year, with the surrounding light grey band indicating the 95% confidence interval. The solid line represents the mean absolute disagreement for bonds issued by firms with ESG disclosure scores above the industry median, accompanied by a dark grey 95% confidence interval band. The vertical line marks Moody's signing the PRI ESG Statement. A post-2016 crossover—highlighted by the shaded area—indicates reduced disagreement for high-disclosure issuers and increased disagreement for low-disclosure issuers.

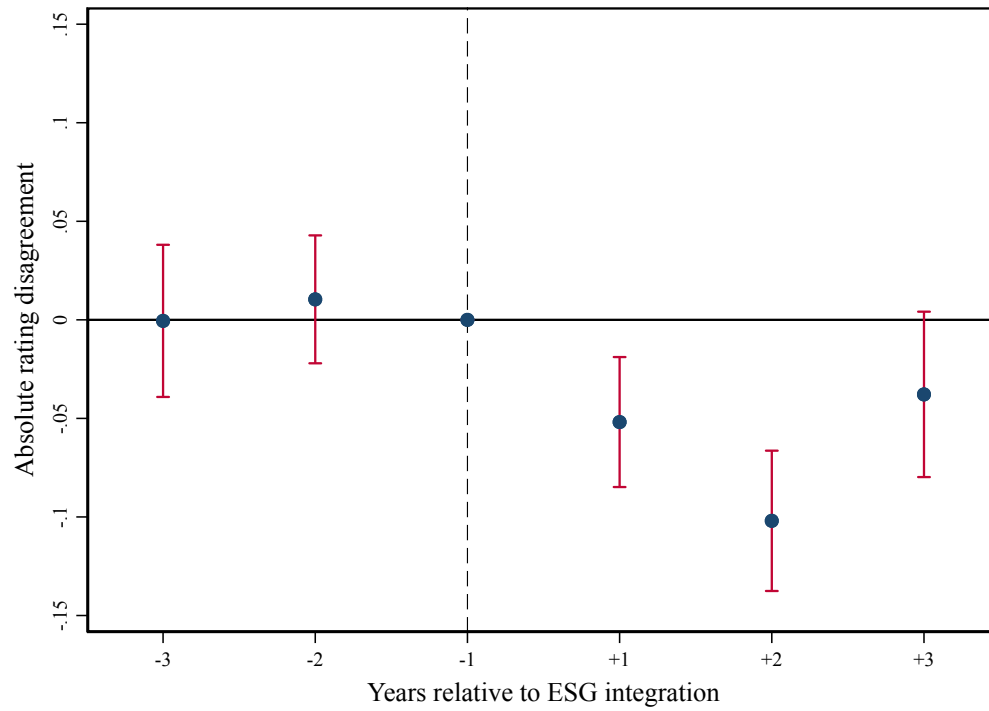


Figure 3. Event-Time Effects of ESG Integration on Absolute Rating Disagreement This figure illustrates the event-time effects of ESG integration on the absolute rating disagreement, using an event-study specification. The base period is the year immediately preceding ESG integration ($t = -1$). Each point in the figure represents the estimated coefficient for a given event time, accompanied by 95% confidence intervals. Standard errors are clustered at the bond level. The estimates are based on the regression model reported in Column (1) of Table 5, restricted to bonds affected by ESG integration between June and December 2016.

Table 1 Credit rating values and distributions

Type	Moody's	Frequency (%)	Fitch	Frequency (%)	Numerical Scale
Investment Grade	Aaa	1.164	AAA	0.674	1
	Aa1	0.342	AA+	0.503	2
	Aa2	2.344	AA	0.970	3
	Aa3	4.798	AA-	4.158	4
	A1	9.109	A+	10.642	5
	A2	11.380	A	17.500	6
	A3	13.209	A-	13.404	7
	Baa1	13.573	BBB+	12.916	8
	Baa2	15.450	BBB	14.953	9
	Baa3	11.161	BBB-	11.159	10
Speculative Grade	Ba1	4.533	BB+	4.204	11
	Ba2	1.700	BB	5.146	12
	Ba3	6.940	BB-	1.610	13
	B1	1.513	B+	0.638	14
	B2	0.855	B	0.507	15
	B3	0.987	B-	0.473	16
	Caa1	0.571	CCC+	0.245	17
	Caa2	0.207	CCC	0.153	18
	Caa3	0.105	CCC-	0.049	19
	Ca	0.053	CC	0.060	20
	C	0.004	C	0.035	21

This table presents the credit ratings and their corresponding frequencies assigned by the rating agencies Moody's and Fitch. To facilitate comparison and analysis, a numerical scale is applied to convert the letter-based ratings into numerical values, based on the interpretation frameworks used by the respective agencies. The sample comprises 7,012 corporate bonds issued by 557 U.S. firms between 2013 and 2018, all of which are rated by both Moody's and Fitch.

Table 2 Descriptive statistics

		25 th -		75 th -		Standard
	Observations	percentile	Median	percentile	Mean	Deviation
Rating disagreements	233,405	0	1	1	0.8283	0.8404
Overrated	233,405	0	0	1	0.4113	0.4921
Underrated	233,405	0	0	0	0.2016	0.4012
ESG disclosure scores	233,405	38.8593	50.2565	59.6016	49.9521	12.8705
ESG Integration	233,405	0	1	1	0.528	0.4992
AT	233,405	9.9747	10.7762	11.723	10.9893	1.5064
TA	233,405	2.9178	20.4094	62.1568	31.0562	29.0684
PRO	233,405	4.9936	8.6877	13.1198	9.7166	6.5392
MB	233,405	129.837	197.938	335.0464	285.198	504.1867
LEV	233,405	20.9621	32.4494	43.4725	32.7036	16.6185
AM	233,405	0	0	12.5913	4.9004	6.1388
MAT	233,405	1.2165	1.9157	2.8901	1.8799	1.1182
CALL	233,405	1	1	1	0.947	0.224
PUT	233,405	0	0	0	0.0077	0.0871
MTN	233,405	0	0	0	0.1791	0.3834

This table shows the descriptive statistics for our sample. All variables are defined in Appendix A, Table A.1.

Table 3 The univariate test of credit rating disagreements from 2013 to 2018

Year	Low ESG disclosure		High ESG disclosure		Difference	P-value
	Mean	Standard Deviation	Mean	Standard Deviation		
	(1)	(2)	(3)	(4)	(5)	(6)
2013	0.734	0.754	0.759	0.843	-0.024**	0.027
2014	0.885	0.848	0.949	0.876	-0.065***	0.000
2015	0.731	.8200	0.876	0.818	-0.146***	0.000
2016	0.791	0.953	0.901	0.888	-0.110***	0.000
2017	0.869	0.825	0.746	0.793	0.122***	0.000
2018	0.845	0.754	0.700	0.782	0.145***	0.000

Bonds issued by firms with ESG disclosure scores below (above) the industry median are classified as having Low (High) ESG disclosure. Column (6) reports the p-value from a hypothesis test evaluating the equality of mean absolute rating disagreements between bonds issued by Low and High ESG disclosure firms. Significance levels are denoted as *p < 0.1; **p < 0.05; ***p < 0.01.

Table 4 The comparison of rating disagreements in pre- and post-ESG incorporation

	Low ESG disclosure	High ESG disclosure	Difference between low/high disclosure groups	P-value
	(1)	(2)	(3)	(4)
Pre-ESG incorporation	0.794	0.893	-0.099***	0.000
Post-ESG incorporation	0.842	0.767	0.075***	0.000
Difference between pre-/post-ESG incorporation groups	-0.048***	0.126***	-0.174***	
P-value	0.000	0.000	0.000	

A bond issuer with an ESG disclosure score below (above) the industry median is classified as having Low (High) ESG disclosure. The Pre- and Post-ESG incorporation periods refer to the time before and after May 2016, when Moody's began integrating ESG information into its credit rating process. Column (4) presents the p-value for the hypothesis test of equality of means between the Low and High ESG disclosure groups across different periods. Significance levels are denoted as * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5 ESG integration and credit rating disagreements-OLS

	Rating disagreement	Rating disagreement	OVERRATED	OVERRATED	UNDERRATED	UNDERRATED
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
ESG integration	-0.0508*** (-3.7431)	-0.0730*** (-5.5931)	-0.0140* (-1.8991)	-0.0230*** (-3.1771)	-0.0150** (-2.3778)	-0.0137** (-2.1786)
AT		-0.4783*** (-11.8264)		-0.2028*** (-11.4644)		0.0490*** (4.0410)
TA		-0.0200*** (-7.3319)		-0.0043*** (-4.1454)		0.0006 (1.0159)
PRO		-0.0014 (-0.6627)		-0.0005 (-0.4620)		0.0046*** (5.9539)
MB		-0.0000 (-1.4569)		0.0000*** (2.6283)		-0.0000*** (-2.6184)
LEV		0.0061*** (3.9384)		0.0024*** (4.6486)		0.0006 (1.1510)
AM		0.0029** (1.9793)		0.0006 (0.8448)		0.0004 (0.5909)
MAT		-0.0008 (-0.0996)		-0.0126*** (-3.1159)		0.0112*** (3.0721)
CALL		-0.0563 (-1.2680)		0.0193 (0.8044)		-0.0258 (-1.3618)
PUT		0.0334 (0.6957)		-0.0034 (-0.0934)		-0.0135 (-1.1231)
MTN		-0.0264 (-0.5449)		0.0214 (0.8771)		0.0550*** (2.5976)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	233,403	233,403	233,403	233,403	233,403	233,403
Adj. R-squared	0.5399	0.5511	0.6525	0.6576	0.6309	0.6332

This table presents bond-level regression analyses examining the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty. One dependent variable, Rating Disagreement, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by Moody's and Fitch. Additionally, we use Overrated/Underrated as dependent variables, where each is a binary indicator set to 1 if Moody's rating value for a bond is higher/lower, respectively, than Fitch's rating value for the same bond, and 0 otherwise. The key independent variable is ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.

Table 6 ESG integration and credit rating disagreements-Logit

	Rating disagreement	Rating disagreement	Overrated	Overrated	Underrated	Underrated
	Ordered logit	Ordered logit	Logit	Logit	Logit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)
ESG integration	-0.1919*** (-10.7445)	-0.3096*** (-17.1072)	-0.1182*** (-4.4409)	-0.2155*** (-7.7916)	-0.1994*** (-5.9491)	-0.2563*** (-7.5212)
AT		-1.8807*** (-57.0927)		-2.0729*** (-40.8010)		0.8091*** (11.9499)
TA		-0.0624*** (-29.2622)		-0.0343*** (-11.8678)		0.0255*** (6.5228)
PRO		-0.0006 (-0.2518)		0.0121*** (3.9012)		0.0723*** (16.1902)
MB		-0.0001*** (-3.6697)		0.0001** (2.2671)		-0.0002*** (-5.4182)
LEV		0.0193*** (16.6473)		0.0356*** (18.3832)		0.0194*** (8.7131)
AM		0.0093*** (7.4176)		0.0056*** (3.0034)		0.0004 (0.1615)
MAT		0.0054 (0.8116)		-0.1355*** (-13.9182)		0.1973*** (16.1546)
CALL		-0.2163*** (-7.4122)		0.2276*** (5.3911)		-0.5183*** (-9.2065)
PUT		0.0630 (1.1393)		-0.0972 (-1.0201)		-0.7115*** (-7.1410)
MTN		-0.0676** (-2.4584)		0.2561*** (5.5137)		1.0803*** (18.0429)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	233,405	233,405	157,549	157,549	107,152	107,152
Pseudo. R-squared	0.3598	0.3691	0.4490	0.4619	0.3886	0.3993

This table presents bond-level logit regression analyses examining the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty. One dependent variable, Rating Disagreement, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by Moody's and Fitch. Additionally, we use Overrated/Underrated as dependent variables, where each is a binary indicator set to 1 if Moody's rating value for a bond is higher/lower, respectively, than Fitch's rating value for the same bond, and 0 otherwise. The key independent variable is ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.

Table 7 ESG integration and credit rating disagreement: the impact of information asymmetry

	Rating disagreement		Rating disagreement		Rating disagreement	
	(1)	(2)	(3)	(4)	(5)	(6)
	Firms with more analysts	Firms with few analysts	Low earning forecast dispersion	High earning forecast dispersion	Small earning forecast error	Large earning forecast error
ESG integration	0.0068 (0.3458)	-0.0789** (-2.4233)	0.0189 (0.9247)	-0.1472*** (-5.2953)	0.0294 (1.5043)	-0.1492*** (-5.4875)
AT	-0.7409*** (-11.6142)	-0.2929*** (-4.6950)	-0.6298*** (-11.9084)	-0.4575*** (-7.1863)	-0.5198*** (-9.5866)	-0.4878*** (-8.0995)
TA	-0.0393*** (-7.9090)	-0.0298*** (-5.6889)	-0.0452*** (-9.1040)	-0.0229*** (-5.2953)	-0.0426*** (-7.8311)	-0.0232*** (-6.0436)
PRO	0.0182*** (7.0815)	0.0018 (0.6118)	0.0149*** (4.6818)	0.0097*** (3.7089)	0.0140*** (4.9627)	0.0048* (1.9415)
MB	0.0000 (0.1543)	-0.0000 (-0.9272)	-0.0001** (-2.2697)	0.0000 (1.3346)	-0.0000** (-1.9951)	0.0000 (0.3239)
LEV	0.0114*** (4.7281)	0.0199*** (6.1037)	0.0162*** (5.4713)	0.0167*** (7.2057)	0.0132*** (4.6797)	0.0165*** (7.5746)
AM	0.0003 (0.1649)	-0.0008 (-0.4054)	0.0009 (0.5497)	-0.0018 (-0.9379)	0.0007 (0.4268)	-0.0020 (-1.1220)
MAT	0.0053 (0.4690)	-0.0017 (-0.1366)	-0.0087 (-0.7517)	0.0137 (1.1674)	-0.0084 (-0.8253)	0.0163 (1.4630)
CALL	-0.0598 (-1.3128)	-0.0886 (-1.3166)	-0.0941** (-2.1486)	-0.0266 (-0.5006)	-0.0765** (-1.9959)	-0.0074 (-0.1707)
PUT	0.0538* (1.6457)	0.0312 (0.9192)	0.1312** (2.5364)	-0.0101 (-0.3872)	0.1110** (2.4760)	0.0003 (0.0111)
MTN	-0.1651* (-1.6692)	0.0041 (0.1037)	-0.0835 (-1.1535)	-0.1779* (-1.7595)	-0.0980 (-1.2979)	-0.1925* (-1.8176)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	48,849	40,479	43,840	44,952	44,315	44,965
Adj. R-squared	0.6803	0.6873	0.6717	0.6686	0.6882	0.6767

This table presents bond-level regression analyses exploring how bond issuers' levels of information asymmetry influence the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty. We employ three measures of information asymmetry: the number of analysts, the dispersion of analyst forecasts, and forecast errors to segment the full sample into subsamples. Firms are classified as having more analysts if the number of analysts following the firm is greater than the industry median; otherwise, they are classified as firms with fewer analysts. Firms with earning forecast dispersion above the industry median are categorized as part of the high earning forecast dispersion sample, while those below the median are included in the low earning forecast dispersion sample. Firms with forecast errors greater than the industry median are placed in the large earning forecast error sample, while those with smaller errors are placed in the small earning forecast error sample. The dependent variable, Rating Disagreement, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by Moody's and Fitch. The key independent variable is ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.

Table 8 ESG integration and credit rating overrated or underrated: impact of information asymmetry

Panel A: Overrated						
	Firms with more analysts	Firms with few analysts	Low earning forecast dispersion	High earning forecast dispersion	Small earning forecast errors	Large earning forecast errors
	(1)	(2)	(3)	(4)	(5)	(6)
ESG integration	-0.0130 (-0.9762)	-0.0344* (-1.8334)	0.0328** (2.4808)	-0.0901*** (-5.3567)	0.0232* (1.8691)	-0.0898*** (-5.7503)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	48,849	40,479	43,840	44,952	44,315	44,965
Adj. R-squared	0.7478	0.6844	0.7332	0.6871	0.7249	0.7080
Panel B: Underrated						
	Firms with more analysts	Firms with few analysts	Low earning forecast dispersion	High earning forecast dispersion	Small earning forecast errors	Large earning forecast errors
	(1)	(2)	(3)	(4)	(5)	(6)
ESG integration	0.0178* (1.8550)	-0.0276** (-1.9995)	-0.0027 (-0.2429)	-0.0172 (-1.4411)	-0.0059 (-0.5200)	-0.0036 (-0.3293)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	48,849	40,479	43,840	44,952	44,315	44,965
Adj. R-squared	0.7731	0.6372	0.6862	0.7557	0.6938	0.7602

This table presents bond-level regression analyses exploring how bond issuers' levels of information asymmetry influence the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty. In panel A, the dependent variable is Overrated as dependent variables, where each is a binary indicator set to 1 if Moody's rating value for a bond is higher than Fitch's rating for the same bond, and 0 otherwise. In panel B, we use Underrated as dependent variables, where is a binary indicator set to 1 if Moody's rating value for a bond is lower than Fitch's rating for the same bond, and 0 otherwise. In both panels, we employ three measures of information asymmetry: the number of analysts, the dispersion of analyst forecasts, and forecast errors to segment the full sample into subsamples. Firms are classified as having more analysts if the number of analysts following the firm is greater than the industry median; otherwise, they are classified as firms with fewer analysts. Firms with earning forecast dispersion above the industry median are categorized as part of the high earning forecast dispersion sample, while those below the median are included in the low earning forecast dispersion sample. Firms with forecast errors greater than the industry median are placed in the large earning forecast error sample, while those with smaller errors are placed in the small earning forecast error sample. The key independent variable is ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively

Table 9 ESG integration and the cost of debt

	credit spread	credit spread
	(1)	(2)
ESG integration	-0.0652** (-2.5022)	-0.0392* (-1.8281)
AT		-0.1532*** (-2.9168)
TA		0.0017 (0.6099)
PRO		-0.0163*** (-3.1435)
MB		0.0000 (0.0150)
LEV		0.0052*** (3.3903)
INTCOV		0.0000* (1.8029)
ROA		-0.0036 (-0.8221)
AM		0.0041*** (3.5252)
MAT		0.2927*** (24.9933)
CALL		0.0709 (1.1707)
PUT		0.0000 (.)
MTN		-0.0795* (-1.7745)
VIX		0.0186*** (8.6447)
Treasury spread		-0.0344 (-0.8978)
Treasury 10y		0.1723*** (5.2438)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
# Observations	3186	3186
Adj. R-squared	0.6134	0.8088

This table presents issue-level regression analyses examining the impact of incorporating ESG metrics into the credit rating process on the cost of debt. We use credit spread as the dependent variable, which is defined as the logarithm of the difference between the yield of the benchmark treasury issue and the issue's offering yield of a bond at issuance. The key independent variable is ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.

Table 10 ESG integration and credit rating disagreements: the role of firm political risk

	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG integration *PRISK	-0.0001** (-2.4671)	-0.0001*** (-2.7183)						
ESG integration *PRISK_ECO			-0.0000* (-1.8884)	-0.0000** (-2.0516)				
ESG integration *PRISK_ENV					-0.0000** (-2.2513)	-0.0000** (-2.0631)		
ESG integration *PRISK_TEC							-0.0000*** (-3.6167)	-0.0000*** (-4.1683)
ESG integration	-0.0501*** (-3.3582)	-0.0673*** (-4.7448)	-0.0513*** (-3.4002)	-0.0696*** (-4.8676)	-0.0532*** (-3.6607)	-0.0722*** (-5.1830)	-0.0516*** (-3.5855)	-0.0685*** (-4.9777)
PRISK	-0.0000 (-1.4993)	-0.0000 (-0.8792)						
PRISK_ECO			0.0000 (0.2093)	0.0000 (1.1628)				
PRISK_ENV					0.0000*** (4.3246)	0.0000*** (4.2815)		
PRISK_TEC							0.0000* (1.7656)	0.0000* (1.7650)
AT		-0.4180*** (-10.1333)		-0.4182*** (-10.1278)		-0.4175*** (-10.1272)		-0.4180*** (-10.1331)
TA		-0.0195*** (-7.0202)		-0.0195*** (-7.0304)		-0.0195*** (-7.0293)		-0.0196*** (-7.0370)
PRO		0.0010 (0.4856)		0.0011 (0.4991)		0.0011 (0.5026)		0.0010 (0.4885)
MB		-0.0000 (-1.2260)		-0.0000 (-1.2140)		-0.0000 (-1.2213)		-0.0000 (-1.1958)
LEV		0.0078*** (4.8858)		0.0078*** (4.8863)		0.0078*** (4.8971)		0.0078*** (4.9006)
AM		0.0020 (1.4002)		0.0020 (1.4044)		0.0020 (1.4081)		0.0020 (1.4041)
MAT		0.0023 (0.2855)		0.0022 (0.2810)		0.0022 (0.2807)		0.0022 (0.2832)
CALL		-0.0696 (-1.6205)		-0.0693 (-1.6112)		-0.0692 (-1.6101)		-0.0692 (-1.6107)
PUT		0.0333		0.0335		0.0336		0.0337

MTN		(0.6918)		(0.6951)		(0.6966)		(0.6984)
		-0.0093		-0.0090		-0.0088		-0.0090
		(-0.1981)		(-0.1919)		(-0.1866)		(-0.1922)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	218390	218390	218390	218390	218390	218390	218390	218390
Adj. R-squared	0.5375	0.5478	0.5374	0.5477	0.5375	0.5478	0.5374	0.5478

This table presents bond-level regressions investigate whether incorporating ESG metrics into the credit rating process affects credit rating uncertainty, particularly under varying levels of political risk exposure. The dependent variable, Rating Disagreement, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by Moody's and Fitch. We use the key independent variables: ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise; PRISK measures the firm-level political risk extracted from textual analysis of quarterly earnings conference-call transcripts; PRISK_ECO measures the firm-level political risk related to Economic Policy & Budget; PRISK_ENV measures the firm-level political risk related to Environment; PRISK_TEC measures the firm-level political risk related to Technology & Infrastructure. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively

Appendix A

Table A.1 Variable definitions

Variable	Definitions
Rating disagreement	The absolute value of the difference between the numerical value of categorical ratings assigned to the same bond issued from Moody's and Fitch
Overrated	An indicator variable as 1 if the rating value of Moody's is larger than Fitch for the same bond, and otherwise 0.
Underrated	An indicator variable as 1 if the rating value of Moody's is smaller than Fitch for the same bond, and otherwise 0.
Credit spread	The logarithm of the difference between the yield of the benchmark treasury issue and the issue's offering yield of a bond at issue time.
ESG disclosure score	The score is equal 0 if a company that do not disclose any ESG information. For companies that disclose a minimal amount of ESG data, the score starts at 0.1, while companies that disclose the complete set of ESG data collected by Bloomberg receive a score of 100.
Issuer-level variables	
Size (AT)	The logarithm of total assets
The ratio of tangible assets (TA)	Net power, plant, and equipment / Total assets
Profitability (PRO)	EBITDA / Total assets
Market-to-book ratio (MB)	The current closing price of stock / The current book value per share
Leverage (LEV)	(Short-term debt + Long-term debt) / Total assets
Return on assets (ROA)	Operating income / Total assets
interest coverage (INTCOV)	Operating income before depreciation and amortization / Interest expense
Bond-level variables	
Outstanding_amount (AM)	The logarithm of the current remaining principal outstanding
Maturity (MAT)	The logarithm of the number of years to maturity
Callable bond dummy (CALL)	An indicator variable, 1 indicating that the issue is callable and 0 otherwise.
Puttable bond dummy (PUT)	An indicator variable, 1 indicating that the issue is puttable and 0 otherwise.
Medium-term note dummy (MTN)	An indicator variable, 1 indicating that the issue is a medium term note and 0 otherwise.
Macroeconomic-level variable	
VIX	The measure of market expectation of volatility for the S&P 500 index
Term spread (T10Y2Y)	The difference in the yields of ten- and two-year Treasury bonds.
10-year Benchmark Treasury rates (DGS10)	10-year Benchmark Treasury rates

Appendix B

Table B.1 Test for whether ESG information consideration reduce rating disagreements considering bond fixed effects

	Rating disagreement	Rating disagreement	Overrated	Overrated	Underrated	Underrated
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
ESG integration	-0.0363*** (-2.7150)	-0.0429*** (-3.2938)	-0.0081 (-1.1218)	-0.0108 (-1.5260)	-0.0138** (-2.2514)	-0.0135** (-2.1978)
AT		-0.3450*** (-9.7213)		-0.1382*** (-8.8988)		0.0343*** (3.1304)
TA		-0.0187*** (-6.6232)		-0.0042*** (-4.1841)		0.0008 (1.3648)
PRO		-0.0021 (-0.9767)		-0.0007 (-0.5902)		0.0034*** (4.2168)
MB		-0.0000 (-1.0943)		0.0000** (2.1803)		-0.0000** (-2.1254)
LEV		0.0034** (2.1206)		0.0022*** (3.8709)		-0.0002 (-0.2970)
AM		0.0000 (.)		0.0000 (.)		0.0000 (.)
MAT		0.0159 (1.3806)		0.0002 (0.0320)		0.0187*** (3.4424)
CALL		0.0000 (.)		0.0000 (.)		0.0000 (.)
PUT		0.0000 (.)		0.0000 (.)		0.0000 (.)
MTN		0.0000 (.)		0.0000 (.)		0.0000 (.)
Bond fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	233,287	233,287	233,287	233,287	233,287	233,287
Adj. R-squared	0.7522	0.7588	0.8009	0.8037	0.7966	0.7973

This table presents bond-level regression analyses examining the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty. One dependent variable, Rating Disagreement, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by Moody's and Fitch. Additionally, we use Overrated/Underrated as dependent variables, where each is a binary indicator set to 1 if Moody's rating value for a bond is higher/lower, respectively, than Fitch's rating value for the same bond, and 0 otherwise. The key independent variable is ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.

Table B.2 Test for whether ESG information consideration reduce rating disagreements considering bond fixed effects

	Rating disagreement	Rating disagreement	Overrated	Overrated	Underrated	Underrated
	Logit	Logit	Logit	Logit	Logit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)
ESG integration	-0.2669*** (-2.7411)	-0.3834*** (-3.9459)	-0.1499*** (-3.9700)	-0.1440*** (-3.6948)	-0.4352*** (-9.0034)	-0.4761*** (-9.7235)
AT		-1.9632*** (-8.7430)		-1.7392*** (-29.0566)		0.4498*** (6.3340)
TA		-0.0701*** (-5.5075)		-0.0406*** (-11.1111)		0.0211*** (3.7908)
PRO		-0.0071 (-0.8037)		0.0008 (0.2161)		0.0622*** (12.2680)
MB		-0.0001 (-1.0692)		0.0001*** (3.3872)		-0.0002*** (-6.3199)
LEV		-0.0038 (-0.4943)		0.0292*** (11.9608)		0.0070*** (2.6596)
AM		0.0000 (.)		0.0000 (.)		0.0000 (.)
MAT		0.0779 (0.7913)		-0.0251 (-0.7118)		0.5127*** (11.8197)
CALL		0.0000 (.)		0.0000 (.)		0.0000 (.)
PUT		0.0000 (.)		0.0000 (.)		0.0000 (.)
MTN		0.0000 (.)		0.0000 (.)		0.0000 (.)
Bond fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	186,846	186,846	66,695	66,695	51,690	51,690
Pseudo. R-squared	0.0270	0.0537	0.0187	0.0446	0.0697	0.0799

This table presents bond-level logit regression analyses examining the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty. One dependent variable, *Rating Disagreement*, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by Moody's and Fitch. Additionally, we use *Overrated/Underrated* as dependent variables, where each is a binary indicator set to 1 if Moody's rating value for a bond is higher/lower, respectively, than Fitch's rating value for the same bond, and 0 otherwise. The key independent variable is *ESG integration* equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.

Table B.3 Test for whether ESG information consideration reduce rating disagreements-S&P.

	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement	Rating disagreement
	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG integration	-0.0774*** (-5.1166)	-0.0827*** (-5.6209)	-0.2500*** (-13.7589)	-0.2715*** (-14.8174)	-0.0989*** (-6.4213)	-0.0949*** (-6.4116)	-0.4891*** (-4.8077)	-0.4090*** (-4.1487)
AT		-0.0404 (-1.0929)		-0.0604* (-1.8149)		-0.0031 (-0.1024)		0.0497 (0.3060)
TA		-0.0131*** (-5.0461)		-0.0481*** (-22.0193)		-0.0109*** (-4.1083)		-0.0526*** (-4.3268)
PRO		-0.0003 (-0.1583)		0.0011 (0.4125)		-0.0024 (-1.2022)		-0.0122 (-1.3020)
MB		0.0000 (1.0267)		0.0002*** (9.7078)		0.0000 (0.5216)		0.0004*** (4.0585)
LEV		0.0133*** (8.3705)		0.0379*** (31.1241)		0.0134*** (7.9371)		0.0407*** (6.8047)
AM		0.0035*** (2.8241)		0.0138*** (11.0625)		0.0000 (.)		0.0000 (.)
MAT		-0.0012 (-0.1870)		-0.0075 (-1.1155)		0.0450*** (3.5798)		0.2879*** (2.7317)
CALL		0.0110 (0.3241)		0.1028*** (3.5177)		0.0000 (.)		0.0000 (.)
PUT		0.0066 (0.1705)		0.0164 (0.2724)		0.0000 (.)		0.0000 (.)
MTN		-0.1031*** (-2.7734)		-0.2895*** (-10.1223)		0.0000 (.)		0.0000 (.)
Firm fixed effects	Yes	Yes	Yes	Yes				
Bond fixed effects					Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	225,064	225,064	225,065	225,065	224,939	224,939	183,256	183,256
Pseudo. R-squared			0.3935	0.3971			0.0877	0.0993
Adj. R-squared	0.5867	0.5933			0.7611	0.7664		

This table presents bond-level OLS and logit regression analyses examining the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty. One dependent variable, *Rating Disagreement*, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by S&P and Fitch. The key independent variable is *DID* equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.

**Table B.4 Test for whether ESG information consideration reduce rating disagreements-
Alternative Estimators.**

Panel A: An alternative estimator (2SDD)						
	Rating disagreement (1)	Rating disagreement (2)	Overrated (3)	Overrated (4)	Underrated (5)	Underrated (6)
ESG integration	-0.0715*** (-4.1178)	-0.0951*** (-5.4376)	-0.0191* (-1.8921)	-0.0289*** (-2.8587)	-0.0220** (-2.4455)	-0.0189** (-2.1055)
Controls	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	233,405	233,405	233,405	233,405	233,405	233,405

Panel B: Restricted sample						
	Rating disagreement (1)	Rating disagreement (2)	Overrated (3)	Overrated (4)	Underrated (5)	Underrated (6)
ESG integration	-0.0463*** (-2.7491)	-0.0643*** (-3.9546)	-0.0114 (-1.2531)	-0.0201** (-2.2671)	-0.0142* (-1.8116)	-0.0128* (-1.6472)
Controls	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	202,920	202,920	202,920	202,920	202,920	202,920

This table reports the average treatment effect (panel A) using the Two-Stage Differences-in-Differences (2SDD) estimator developed by Gardner et al. (2025), which explicitly accommodates staggered treatment adoption and the impact of incorporating ESG metrics into the credit rating process on credit rating uncertainty, focusing exclusively on treated bonds observed between June and December 2016 and never-treated bonds within the sample (panel B). One dependent variable, Rating Disagreement, is defined as the absolute difference between the numerical values of categorical ratings assigned to the same bond by Moody's and Fitch. Additionally, we use Overrated/Underrated as dependent variables, where each is a binary indicator set to 1 if Moody's rating value for a bond is higher/lower, respectively, than Fitch's rating value for the same bond, and 0 otherwise. The key independent variable is ESG integration equals 1 if a bond rating is observed after May 2016 and the corresponding ESG disclosure score exceeds the industry median in that year, and 0 otherwise. Detailed definitions of all variables are provided in Appendix Table A.1. Heteroskedasticity-consistent standard errors are clustered at the bond level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-levels, respectively.