When Numbers Speak: The Usefulness of ESG Indicators in Credit Rating Reports

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Abstract

This study examines S&P Global Ratings' introduction in 2021 and discontinuation in 2023 of numeric, credit-related ESG indicators in rating reports. Using issuer reports from 2017–2024, we employ difference-in-differences designs around the disclosure changes. We find that the adoption of ESG indicators is associated with improved bond liquidity, reduced pricing uncertainty, and stronger bond-market responsiveness. More favorable indicators are associated with positive bond returns around report releases and higher contemporaneous and next year credit ratings. The indicators are also forward-looking: more favorable ESG credit indicators are associated with higher subsequent operating margins and lower earnings volatility. Finally, numeric indicators partly substitute for narrative discussion, though adverse scores elicit more extensive explanation. Overall, the evidence suggests that ESG indicators improve issuers' information environment.

Keywords: ESG credit indicators, Credit spreads, Bond price reactions, Credit ratings, Financial performance

JEL Codes: G10, G14, G20, G32

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1 Introduction

Environmental, social, and governance (ESG) considerations have moved from the periphery of corporate disclosure to a central input in risk assessment across capital markets (Berg et al., 2022; SEC, 2024). Credit rating agencies sit at the core of this shift because their opinions shape the cost and allocation of debt capital and provide a focal signal for fixed-income investors. In September 2021, S&P Global Ratings changed the way it communicates ESG-related credit risk by supplementing the ESG discussion in issuer credit rating reports with numeric, pillar-level ESG credit indicators for publicly rated entities in selected sectors and asset classes. These indicators report separate scores for environmental, social, and governance factors on a common scale that is explicitly intended to summarize the extent to which ESG considerations influence S&P's credit analysis. By translating complex qualitative assessments into standardized signals, such indicators have the potential to improve the efficiency with which ESG-related credit risk is incorporated into bond prices.

Less than two years later, in August 2023, S&P discontinued publishing these ESG credit indicators in its rating reports (S&P Global, 2023). S&P emphasized that narrative paragraphs remain the most effective way to convey detailed and transparent information on ESG factors that are material to credit risk, and that removing the numeric indicators would not change its underlying ESG principles or analytical approach. This decision occurred amid intensified regulatory scrutiny and political backlash against ESG practices, raising the reputational and legal risks of explicitly labeling ESG metrics. The combination of a discrete adoption and an equally discrete withdrawal by the same agency, within the same reporting product, creates a setting-specific tension about the informational role of numeric ESG disclosure inside the credit rating process. On the one hand, numerical indicators may improve informational efficiency in bond markets by offering a concise and comparable summary of ESG-related credit risks. On the other hand, their visibility may subject credit rating agencies to meaningful political and reputational costs linked to explicit ESG labeling. The heightened scrutiny of ESG practices thus suggests that rating agencies may have incentives to reduce the prominence of visible ESG metrics even when such indicators are informationally valuable, reflecting broader tensions between informational efficiency and the political economy of ESG disclosure.

If the indicators provided investors with a low-cost, credit-impact–oriented summary that improved the interpretability and comparability of ESG considerations, their introduction should have strengthened price discovery in debt markets and clarified how ESG enters credit opinions, while their removal should have reduced transparency. If instead the indicators were too coarse to capture context-dependent risks, or if their salience encouraged users to substitute away from the underlying narrative reasoning, then publishing them may have added little incremental information or even impaired communication, and discontinuation would be consistent with removing a potentially misleading signal (Stein, 2002; Ronzani and Gatzweiler, 2022).

This paper examines whether S&P's ESG credit indicators, as implemented in the credit rating framework, provide incremental, credit-relevant information beyond narrative ESG disclosures and external ESG ratings.[1] We construct a report–level panel from issuer credit rating reports. From each report, we manually collect S&P's ESG credit indicators and extract the ESG (Environmental, Social, and Governance) section. These data allow us to measure how ESG considerations are communicated within the credit assessment process. We further merge these reports with bond data from TRACE, FISD and Datastream to constract bond–level measures of bond-market trading frictions and bond-price reactions. Using these data, we address four research questions that are central to the current debate.

First, do ESG credit indicators affect the bond-market information environment? To address this question, we use bond-level data and implement difference-in-differences (DiD) designs to examine changes in secondary-bond-market trading frictions, pricing uncertainty,

[1] S&P's ESG credit indicators are not sustainability ratings and do not constitute an S&P Global Ratings ESG Evaluation.

and bond-market responsiveness around S&P's 2021 adoption and 2023 withdrawal of ESG credit indicators. The DiD specifications relate multiple measures of secondary-bond-market activity to the introduction and subsequent removal of the indicators, comparing bonds associated with ESG-covered reports to matched bonds without such coverage.[2] We find that the adoption of ESG credit indicators is associated with lower effective bid–ask spread, lower bid–ask spread volatility, lower G-spread volatility, and stronger bond-market responsiveness for ESG-covered bonds relative to non-covered bonds. Taken together, the results are consistent with ESG credit indicators reducing information frictions and improving the bond-market information environment.

By contrast, the effects of their withdrawal are weaker and less conclusive for spread-volatility measures. This pattern is consistent with the possibility that market participants continue to rely on previously disclosed ESG credit assessments after the indicators are removed. It is also consistent with ESG-related credit risks being relatively persistent over short horizons, allowing previously disclosed indicators to retain informational value. However, we observe attenuated bond -market responsiveness for ESG-covered firms following withdrawal, suggesting a diminished immediate informational impact in the absence of standardized, prominently displayed ESG indicators. This pattern highlights the role of numeric indicators as salient, decision-useful signals that help investors quickly interpret and act on ESG-related credit information.

We also estimate regressions of bond price reactions by relating secondary-market bond cumulative abnormal returns (CARs) around the credit rating report issuance date to ESG credit indicators. Specifically, we control for ESG narrative tone and third-party LSEG ESG scores to isolate the incremental information content uniquely conveyed by the ESG credit indicators. Consistent with the indicators conveying value-relevant information, more favorable ESG credit indicators are associated with significantly higher bond-market CARs

[2]To improve covariate balance and mitigate selection concerns, we employ entropy balancing within each DiD specification, using firm fundamentals including leverage, accounting loss, firm size, market-to-book ratio, and profitability.

around report issuance, even after controlling for ESG narrative tone and LSEG ESG scores. Furthermore, we show that these market reactions are not mechanically driven by or conditional on contemporaneous changes in credit ratings. Overall, these results are consistent with improved price discovery when the indicators are displayed, and with bond investors incorporating the credit-relevant ESG signal embedded in the indicators. These results suggest that prominently presented ESG indicators reduce information frictions for fixed-income investors beyond what narrative-only discussion and third-party ESG scores can achieve.

Second, are S&P's ESG credit indicators associated with levels and changes in credit ratings? Using report–level data, we estimate regressions that relate ESG credit indicators to contemporaneous and future S&P credit ratings. We again control for ESG narrative tone and third-party LSEG ESG scores to assess the incremental, distinct information conveyed by the indicators. We document that more adverse ESG credit indicators are associated with lower current and next-year rating levels. Furthermore, ESG credit indicators are more strongly related to current and future credit ratings than either narrative tone or third-party ESG scores. These findings are consistent with the indicators serving as transparent, quantitatively salient summaries of the ESG-related component of S&P's credit assessments and being more tightly integrated into the rating process than alternative ESG measures.

Third, are the indicators informative about subsequent firm financial performance, including profitability and risk? We test this by relating ESG credit indicators to next-year financial outcomes, specifically operating margins and earnings volatility. We find that ESG credit indicators are statistically significant predictors of both: more favorable indicators are associated with higher subsequent operating margins and lower earnings volatility. In comparative regressions, ESG credit indicators retain significant predictive power for future operating performance and risk after controlling for ESG narrative tone. This evidence suggests that the indicators embed forward-looking assessments of firms' financial performance trajectories and capture financially relevant ESG information that is not fully reflected in qualitative narratives.

Fourth, do ESG credit indicators substitute for or complement the content of ESG narratives in credit rating reports? To study this question, we first exploit the adoption and subsequent withdrawal of ESG credit indicators in DiD tests that examine changes in the volume and composition of narrative content within the ESG section. We find that the adoption of ESG credit indicators is associated with a decline in both the volume of the ESG section and the prevalence of forward-looking ESG statements, consistent with substitution in the use of narrative disclosure. Within the scoring regime, we then estimate cross-sectional regressions that relate ESG credit indicators to the share and characteristics of ESG narrative content. These regressions show that more adverse ESG credit indicators are positively associated with the intensity of ESG-related discussion. This pattern suggests substitution at the extensive margin but complementarity at the intensive margin.

By bringing evidence to bear on these four questions, we inform the ongoing policy and market debate over the role of numeric ESG credit indicators in credit rating reports. Overall, our evidence suggests that these indicators enhance the transparency and usefulness of rating reports by improving the secondary-bond-market information environment and conveying incremental, credit-relevant information beyond ESG narratives and third-party ESG ratings.

This paper makes contributions to three streams of literature. First, this paper adds to the literature on the role of ESG in credit risk assessment. Prior studies establish correlations between ESG performance and easier access to finance (Cheng et al., 2014; Kim et al., 2014). Building on prior research, our analysis provides direct evidence on how S&P, as a prominent CRA, integrates ESG considerations into its credit rating assessments. Our findings have implications for both CRAs and regulators. For CRAs, the results indicate that ESG credit indicators complement ESG narratives in credit rating reports: a mixed-mode approach—combining numeric indicators with focused qualitative analysis—appears to provide more transparent and decision-useful communication than either modality alone. For regulators, the results suggest that incorporating ESG credit indicators into credit rating disclosures can enhance price discovery, in turn, improving market efficiency. This finding implies that regulatory guidance or policies promoting the use of standardized, credit-oriented ESG indicators in credit rating reports could strengthen the informational value of these reports, facilitate informed investment decisions, and foster better integration of ESG considerations into capital markets.

Second, we contribute to the literature on the informativeness of ESG ratings. Prior research documents substantial divergence across external ESG ratings arising from differences in scope, measurement, and aggregation (Berg et al., 2022), and shows that such divergence is associated with higher return volatility and a reduced likelihood of obtaining external financing (Christensen et al., 2022). We extend this literature by showing that ESG ratings produced by different providers are designed for distinct purposes and audiences, and thus are not directly comparable. S&P's ESG credit indicators are explicitly credit-related and produced within the credit rating process; their primary audience is fixed-income investors, creditors, and prudential regulators who focus on the implications of ESG factors for default risk and creditworthiness. By contrast, third-party scores such as LSEG ESG ratings are intended to capture firms' overall ESG performance and are targeted at a broader set of users—including equity and multi-asset investors, asset managers, and other stakeholders—who use them for portfolio screening, benchmarking, and sustainability reporting. As a result, these ESG measures are conceptually distinct and are expected to convey different information. Consistent with this view, our evidence shows that S&P's credit-related ESG indicators, produced by an issuer-paid CRA with an information advantage, convey information that is not subsumed by third-party, investor-oriented ESG ratings (e.g., LSEG ESG scores). These indicators serve as an additional information source for capital markets: they are associated with a meaningfully improved information environment in the secondary bond market, tightly related to credit rating levels, and informative about subsequent firm financial performance.

Finally, this paper adds to the emerging literature on the informational content of credit rating reports. Kiesel and Kisgen (2024) provide evidence that the content of credit rating reports significantly influences market reactions and predicts future rating changes, emphasizing the importance of qualitative factors in credit risk assessment reports. Agarwal et al. (2016) and Löffler et al. (2021) show that net negative tone in rating actions reports predicts future downgrades.[3] Jiang et al. (2024) use topic modeling techniques to analyze liquidity and financial performance topics in rating actions reports, finding that these textual elements enhance the explanatory power of market reactions to credit rating actions and predict default likelihood and financial performance. Extending this literature, we show that ESG credit indicators in credit rating reports have predictive power for future credit ratings and credit spread adjustments, and provide incremental information to the bond market.

2 Institutional background

2.1 Development and methodology of S&P ESG credit indicators

Since September 2021, S&P introduced ESG credit indicators for companies in the corporate and infrastructure, banking, and insurance sectors. Subsequently, in the spring of 2022, the implementation of these indicators was extended to additional asset classes. The indicators are disclosed in the ESG section of issuer credit rating reports and are reported separately for the E, S, and G dimensions.[4]

ESG credit indicators are based on a five-point scale, where each indicator reflects the degree

[3]Credit rating reports provide more comprehensive information, whereas rating action reports are shorter in length and primarily focused on announcing and explaining specific rating changes. In this paper, we focus primarily on credit rating reports.

[4]Illustrative examples of ESG credit indicator disclosures are presented in Figure 1. For each pillar, S&P reports a numeric indicator, beneath which it lists brief phrases summarizing the key ESG-related risk factors; more detailed qualitative discussion elaborating on these risks is then provided further below in the ESG section to justify each indicator.

of credit impact associated with ESG factors.[5] An indicator of 1 denotes a positive credit impact, while 2 represents a neutral impact.[6] Indicators of 3, 4, and 5 indicate progressively negative impacts, with 3 suggesting a moderately negative impact, 4 indicating a negative impact, and 5 is a strongly negative impact. This scoring framework is intentionally skewed toward negative impacts, reflecting the view that ESG factors relevant to credit ratings are more likely to exert adverse effects than positive effects. The S&P's introduction of ESG credit indicators is intended to enhance transparency by clearly identifying the role of ESG factors within S&P's credit rating methodology (S&P Global, 2022). This is achieved by isolating their credit impact from non-ESG considerations that also affect credit ratings.

In evaluating environmental credit indicators, S&P integrates climate transition risks, physical risks, natural capital, and risks associated with waste, pollution, and biodiversity, and other environmental factors into its rating analyses.[7] These factors are examined through both forward-looking qualitative and quantitative methodologies. Environmental risks are considered particularly significant and often exert a pronounced impact on specific industries, such as the power sector, including the oil and gas industries. While industry-specific risks play a crucial role in assessing environmental factors, they represent only one component among several elements within S&P's comprehensive credit rating framework. Entities may encounter adverse environmental impacts in its industry risk assessment, while these negative factors may be offset by favorable environmental influences tied to their competitive positioning.

S&P social credit indicators are primarily entity-specific rather than industry-specific. They consider health and safety, social capital, human capital, and other social factors when

[5]ESG credit indicators are not published for entities with credit ratings of "SD" (selective default) or "D" (default).

[6]A neutral ESG credit indicator (e.g., E-2 for environmental, S-2 for social, or G-2 for governance) does not indicate an absence of ESG relevance. Rather, it indicates that ESG factors currently have a neutral influence on the credit rating analysis. As a factor that negatively impacts the E, S, or G credit indicator might be offset by another factor that positively impacts the indicator.

[7]Illustrative examples of how S&P incorporates these environmental factors into its credit rating analyses are provided in the Online Appendix. Additional examples for the social and governance factors discussed below are likewise presented in the Online Appendix.

evaluating social credit indicators. The significance of these factors is more pronounced when evaluating an entity's direct exposure to and management of them, which often relates to its staff, community relationships, and customer base. However, one exception is the mining industry, where social risks such as community opposition and safety concerns exert a moderately negative impact.

Governance credit indicators are closely associated with S&P's Management and Governance (M&G) criteria scores. Governance considerations within the M&G framework include factors such as board effectiveness, ownership structure, risk management, internal control, and reporting transparency. Some management-related subfactors are also deemed relevant to governance, including strategic positioning, organizational effectiveness, risk, and financial management.

2.2 Controversy and theoretical perspectives on ESG credit indicators

There has been considerable debate regarding the usefulness of numeric ESG measures in credit risk assessment. Proponents argue that ESG credit indicators enhance the transparency and decision usefulness of rating reports by distilling complex ESG assessments into standardized and comparable metrics. In practice, many institutional investors, asset managers, and pension funds have expressed support for ESG indicators as tools for benchmarking, transparency, and the early identification of ESG-related risks, even when such indicators do not directly determine credit ratings (see Appendix 1.A).

From an information economics perspective, numeric ESG indicators may improve market efficiency by lowering the cognitive and processing costs associated with interpreting complex disclosures. Under theories of limited attention and rational inattention, concise numeric signals may help investors facing constraints in processing lengthy narrative disclosures to more readily focus on credit-relevant ESG information that might otherwise be overlooked (e.g., DellaVigna and Pollet, 2009; Hirshleifer and Teoh, 2003; Hirshleifer et al., 2009). Therefore, standardized numeric ESG indicators may lower investors' information acquisition and integration costs and mitigate information asymmetry. Beyond reducing processing costs, standardized ESG indicators may also serve as an effective communication device that translates nuanced qualitative judgments into a common scale that is easier to interpret across heterogeneous market participants (Jordan et al., 2018). By rendering ESG assessments more legible and comparable, such indicators can facilitate coordination of beliefs and improve the incorporation of ESG risks into credit pricing. Moreover, by explicitly mapping ESG considerations onto a credit-impact scale, numeric ESG indicators may reduce ambiguity about whether—and to what extent—ESG issues influence credit assessments, thereby strengthening the credibility of credit rating agencies' claims regarding ESG integration.

Opponents, however, contend that assigning a single numeric score to ESG pillars risks oversimplifying risks that are inherently multifaceted and highly context dependent. Critics—including investors, regulators, and governance experts—argue that ESG scores often suffer from limited comparability, opaque methodologies, and excessive aggregation across heterogeneous dimensions. They further caution that prominent numeric indicators may crowd out qualitative judgment, obscuring firm-specific materiality and potentially adding noise rather than clarity to credit assessments (see Appendix 1.B).

Theory on multidimensional performance measurement and information aggregation suggests that compressing rich qualitative assessments into a coarse metric can generate material information loss and measurement error, especially when underlying dimensions are imperfectly observable and vary in materiality across firms and sectors (e.g., Feltham and Xie, 1994). More critically, critics argue that salient and visually intuitive indicators may trigger what Ronzani and Gatzweiler (2022) term the "lure of the visual," whereby simplified metrics convey a false sense of precision and encourage reliance on the headline score rather than the underlying reasoning. In this view, a prominent numeric ESG indicator can crowd out the qualitative judgment and contextual discussion embedded in narrative disclosures, which are central to evaluating long-horizon, low-frequency ESG risks. Relatedly, the soft-versus-hard information perspective suggests that attempts to codify qualitative assessments into rigid quantitative formats can discard precisely the nuance and judgment that make such information decision useful (Stein, 2002). These concerns also echo Goodhart-type critiques: once a numeric score becomes a salient benchmark, it may be strategically managed or "gamed," inducing superficial box-ticking behavior that weakens the link between reported ESG indicators and fundamental credit risk (Berg et al., 2022). From this perspective, ESG credit indicators may mislead investors not because ESG risks are irrelevant, but because excessive simplification can mask complexity and create an illusion of objectivity.

Consistent with these concerns, market commentary surrounding S&P's ESG credit indicators frequently noted investor confusion regarding whether the indicators affected headline credit ratings,[8] despite repeated clarifications by S&P that the indicators are intended as informational supplements rather than determinants of credit ratings (S&P Global, 2021, 2022). Notably, ESG credit indicators are applied after credit ratings are determined and cannot independently trigger rating upgrades or downgrades.

The controversy intensified in August 2023, when S&P announced that it would cease publishing ESG credit indicators in its rating reports (S&P Global, 2023). S&P justified this decision by emphasizing that narrative discussion remains the most effective means of conveying detailed and transparent information about ESG factors that are material to its credit analysis, and that the removal of numeric indicators would not alter its ESG principles, criteria, or underlying analytical framework. S&P's decision coincided with heightened regulatory scrutiny and political opposition to ESG practices, including a 2022 investigation by U.S. state attorneys general as part of a broader anti-ESG campaign,[9] which increased

[8]See Mark Segal, "S&P Removes ESG Indicators from Credit Rating Reports," *ESG Today*, August 9, 2023.

[9]See "Paxton Launches Investigation into S&P Global's Use of ESG Factors in Credit Ratings, Potentially Violating Consumer Protection Laws," *Ken Paxton Attorney General of Texas*, September 28, 2022.

the reputational and legal risks associated with explicit ESG labeling (see Appendix 1.C).

From an economic perspective, the withdrawal of ESG credit indicators highlights a tension between informational efficiency and the political or reputational costs of salient ESG labeling. The controversy surrounding ESG metrics suggests that credit rating agencies may face non-trivial political and reputational costs when ESG considerations are presented in highly visible quantitative form. As a result, agencies may have incentives to continue incorporating ESG risks into credit analysis while presenting those assessments primarily through narrative disclosure rather than explicit numeric labels. The withdrawal of ESG credit indicators has therefore been widely interpreted as a strategic reframing of ESG disclosure—preserving ESG integration while softening its outward presentation—reflecting broader tensions surrounding the role of ESG metrics in financial markets.

From an information-theoretic perspective, the withdrawal of numeric indicators could either (i) improve welfare if the indicators were noisy, biased, or misleading, or (ii) reduce welfare if they provided a low-cost, decision-useful summary that complemented narrative analysis. Aligned with critics' views, one interpretation is that the indicators added limited incremental content beyond the narratives and that their discontinuation implicitly acknowledges the constraints of highly compressed ESG metrics. An interpretation of the second possibility, closer to proponents' views, is that removing a clear numeric mapping from ESG assessments to credit impact reduces transparency: if narrative disclosure alone is sufficient for investors to understand credit risk, then, by analogy, one might question why traditional letter-based credit ratings themselves remain necessary in addition to narrative credit opinions.

2.3 ESG factors, bond markets, and credit ratings

Prior evidence demonstrates that ESG performance materially influences firms' credit risk and financing outcomes, with direct implications for bond pricing. Empirical evidence shows that strengthened governance reduces perceived risk and benefits bondholders (Klock et al., 2005). Green bonds, which signal environmental stewardship, exhibit lower yields than conventional bonds (Tang and Zhang, 2020). Moreover, Amiraslani et al. (2023) find that environmental and social metrics can yield greater bond market benefits than governance alone, particularly during financial crises, highlighting the critical role of ESG performance in shaping bond market perceptions. Taken together, this evidence suggests that when ESG information is salient and viewed as credit relevant, it is incorporated into bond prices through its implications for firms' perceived default risk and financing costs. By integrating ESG factors into credit assessments, investors and rating agencies can form a more comprehensive view of a firm's risk profile.

As ESG considerations have grown increasingly significant in capital markets and corporate strategy (Christensen et al., 2021; Dyck et al., 2023), the determinants of credit ratings extend beyond traditional financial metrics to encompass ESG factors, reflecting a broader recognition that environmental degradation, social inequalities, and governance failures are salient drivers of credit risk. Investors therefore seek to understand how ESG risks translate into credit risk and pricing, and a growing body of evidence links ESG performance to financing conditions and default risk. For example, both bank and bond investors appear to price ESG-related exposures, with firms exhibiting weaker ESG profiles often facing higher funding costs or more restrictive terms, consistent with risk-based pricing (Christensen et al., 2021).

ESG credit indicators embedded in issuer credit rating reports may serve as signals that highlight ESG information more closely tied to credit risk. These indicators provide a structured summary of ESG-related credit risks within S&P's established rating framework. By summarizing ESG considerations in a standardized and easily processed format, they may shape how investors interpret and incorporate ESG-related information in bond markets, over and above narrative disclosures alone. If these indicators capture the materiality of ESG considerations for the rating outcome, they should be reflected in both contemporaneous and future credit ratings, to the extent that ESG risks persist over time. The forward-looking aspect of S&P credit ratings further motivates the expectation that ESG credit indicators, which encapsulate enduring risk dimensions, may influence credit ratings beyond the current reporting cycle.

3 Data and methodology

3.1 Data and sample

We obtain credit rating reports from S&P Capital IQ RatingsXpress, bond transaction data from TRACE, bond characteristics from FISD, bond daily trading data from Datastream, and financial data from Compustat. In addition, we obtain the LSEG ESG score from LSEG ESG. The sample period spans from 2017 to 2024.

Appendix 3 presents the procedure used to construct the sample for the empirical analyses. We begin by collecting all credit rating reports issued by S&P between January 2017 and July 2024 from S&P Capital IQ RatingsXpress, totaling 44,394 reports. These reports are matched to the Capital IQ Identifier Linking Query using the report ID, and observations with missing firm identifiers (GVKEY) are excluded. This process results in 6,465 reports covering 1,448 unique firms. The resulting dataset is then merged with Compustat. To maximize the number of retained observations, we exclude firms with missing values for any variables other than *Tangibility*. This yields the main sample of 5,325 observations for 1,197 unique firms. Among the 1,897 S&P credit rating reports issued for 952 unique firms between September 2021 and August 2023—the period during which S&P published ESG credit indicators—922 reports (covering 632 unique firms) contain published S&P ESG credit indicators.

3.2 Research design

S&P introduced ESG credit indicators for publicly rated entities across specific sectors and asset classes in their credit rating reports in September 2021, but ceased publishing these indicators in August 2023. Because S&P provided ESG credit indicators only for entities within certain sectors and asset classes, and it is unclear whether these indicators were selectively published for particular firms, our first analysis examines the determinants of S&P's decision to include ESG credit indicators.

We classify firms into two groups. The ESG-credit-indicator-covered group comprises firms for which S&P published ESG credit indicators at least once between September 2021 and August 2023, whereas the non-covered group includes firms for which no ESG credit indicators were published during this period. The empirical specification for this analysis is as follows:

$$\begin{aligned} \mathit{ESG\_Covered}_{i,t} = \beta_1 &+ \beta_2\, \mathit{Leverage}_{i,t} + \beta_3\, \mathit{Loss}_{i,t} + \beta_4\, \mathit{MktCap}_{i,t} + \beta_5\, \mathit{Mkt\_to\_Book}_{i,t} \\ &+ \beta_6\, \mathit{ROA}_{i,t} + \mathit{Industry\,FE} + \mathit{Year\,FE} + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where *ESG_Covered* is an indicator variable equal to one for firms with ESG credit indicators published at least once by S&P between September 2021 and August 2023, and zero otherwise. The determinants include firm fundamentals: leverage (*Leverage*), accounting loss (*Loss*), firm size (*MktCap*), market-to-book ratio (*Mkt_to_Book*), and profitability (*ROA*). We also include Fama–French 12 industry fixed effects to capture systematic differences in coverage across industries, as well as year fixed effects to absorb common time trends. Variable definitions are provided in Appendix 2. To improve comparability between ESG-credit-indicator-covered and non-covered observations and mitigate concerns about differential trends, we implement entropy balancing (Hainmueller, 2012) to construct a matched sample based on the firm-fundamentals controls used in Equation (1) (*Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*). (2a) and (2b).[10]

[10] As a robustness check, we implement alternative matching procedures. Specifically, we apply entropy

For the main analysis, we exploit two discrete changes in S&P's disclosure of ESG credit indicators: their introduction in September 2021 and their discontinuation in August 2023. To evaluate the effects of indicator introduction, we define the pre-adoption period as the period prior to September 2021 and the adoption period as September 2021–August 2023. To assess the implications of indicator removal, we define the pre-abandonment period as September 2021–August 2023 and the abandonment period as the years after August 2023. We estimate DiD specifications around both events. The baseline models are:

$$\begin{aligned} \mathit{Bond\_Market\_Outcome}_{i,t+1} = \beta_1 + \beta_2\, \mathit{Adopt}_t \times \mathit{ESG\_Covered}_i + \beta_3\, \mathit{Adopt}_t \\ + \gamma\, \mathit{Controls} + \mathit{Firm\ FE} + \mathit{Year\ FE} + \epsilon_{i,t}, \end{aligned} \tag{2a}$$

$$\begin{aligned} \mathit{Bond\_Market\_Outcome}_{i,t+1} = \beta_1 + \beta_2\, \mathit{Abandon}_t \times \mathit{ESG\_Covered}_i + \beta_3\, \mathit{Abandon}_t \\ + \gamma\, \mathit{Controls} + \mathit{Firm\ FE} + \mathit{Year\ FE} + \epsilon_{i,t}, \end{aligned} \tag{2b}$$

where *Adopt* equals one if the report date falls between September 2021 and August 2023, and zero if the report date is prior to September 2021, and *Abandon* equals one if the report date is after August 2023, and zero if the report date falls between September 2021 and August 2023.

In the bond-market information environment tests, *Bond_Market_Outcome* is alternatively defined as: (i) the mean and median effective daily relative bid–ask spread over the one-year period following the report release, *Avg_BidAsk (t+1)* and Med_BidAsk (t+1) Schestag et al. (2016), (ii) the standard deviation of the daily quoted bid–ask spread over the one-year period following the report release, *Spread_Vol (t+1)*, and (iii) the standard deviation of the daily quoted G-spread over the same period, *GSpread_Vol (t+1)*. These variables are

balancing using the full set of control variables included in the corresponding regressions and also construct a matched sample using propensity score matching (PSM) based on the same firm characteristics employed in the main entropy-balancing tests (*Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*). The results from these alternative matching approaches are reported in the Online Appendix.

constructed at the bond–report level to capture changes in trading frictions and credit risk perceptions following the introduction or removal of ESG credit indicators. In these specifications, we include firm and year fixed effects to control for time-invariant firm heterogeneity and common time trends.[11]

Control variables include firm fundamentals, report-level characteristics, and S&P credit ratings. In addition, we follow Amiraslani et al. (2023) and control for bond characteristics relevant to the dependent variables, including the firm coverage ratio (*Coverage_Ratio*), bond coupon rate (*Coupon*), time to maturity (*LnMaturity*), and bond offering amount (*Offering_Amount*).

To assess the intensity of bond-market responsiveness, we define $Bond\_Market\_Outcome$ as the absolute value of cumulative abnormal bond returns around the credit rating report filing date, *AbsCAR[*$-3, 3$*]* (e.g., Bao et al., 2011; Bessembinder et al., 2006). We use these bond–report level measures to capture changes in the magnitude of market reactions associated with the introduction or removal of ESG credit indicators. In these regressions, we include year fixed effects to absorb common time trends. Control variables include firm fundamentals, report-level characteristics, and S&P credit ratings.

To improve comparability between ESG-credit-indicator-covered and non-covered observations and mitigate concerns about differential trends, we implement entropy balancing (Hainmueller, 2012) to construct a matched sample based on the firm-fundamentals controls used in Equation (1) (*Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*). (2a) and (2b).[12]

Despite the growing prominence of ESG considerations in credit analysis, there is little empirical evidence on the informational value of ESG credit indicators disclosed by credit

[11] In addition to the quoted-price data obtained from Datastream used in the main analysis, we also obtain transaction-level bond data from TRACE to measure the bond-market information environment. The corresponding results are reported in the Online Appendix.

[12] As a robustness check, we implement alternative matching procedures. Specifically, we apply entropy balancing using the full set of control variables included in the corresponding regressions and also construct a matched sample using propensity score matching (PSM) based on the same firm characteristics employed in the main entropy-balancing tests (*Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*). The results from these alternative matching approaches are reported in the Online Appendix.

rating agencies.[13] To address this gap, we investigate how ESG credit indicators contained in SP credit rating reports affect bond-price reactions. Given that ESG credit indicators were published only between September 2021 and August 2023, our primary analysis focuses on this period. We estimate the following empirical specification:

$$CAR[-3,3]_{i,t} = \beta_1 + \beta_2\, ESGScore_{i,t} + \gamma\, Controls + Year\ FE + \epsilon_{i,t}, \tag{3}$$

where the main variable of interest, *ESGScore*, is the average of the environmental, social, and governance credit indicators manually collected from S&P credit rating reports. Because higher values of S&P's ESG credit indicators correspond to more adverse ESG credit impacts, we invert the measure so that higher values of *ESGScore* indicate more favorable ESG credit assessments, facilitating interpretation.

The bond price reactions are measured as cumulative abnormal bond returns around the credit rating report filing date, *CAR [-3, 3]*. We construct the variable following Defond and Zhang (2014), with detailed definitions provided in Appendix 2. In these event-study specifications, year fixed effects are included to absorb common time trends, and the regressions control for firm fundamentals, S&P credit ratings, and report characteristics.

To isolate the informational content of ESG credit indicators, we control for *ESGTone*, a sentiment measure for ESG-related sentences in the ESG section of S&P credit rating reports, constructed using the FinBERT model at the sentence level.[14] We also estimate Equation (3) with third-party ESG performance metrics from LSEG, *LSEG_ESGScore*, which are widely used in the investment community and provide an independent, externally assessed view of firms' ESG profiles. Controlling for *ESGTone* and *LSEG_ESGScore* allows us to benchmark

[13] Although S&P discontinued publishing ESG credit indicators, the other two major CRAs, Moody's and Fitch, continue to report similar indicators.

[14] In the Online Appendix, we replace *ESGScore* with its disaggregated components, *EScore*, *SScore*, and *GScore*, which represent the individual environmental, social, and governance credit indicators, respectively. We also replace *ESGTone* with disaggregated tone measures *ETone*, *STone*, and *GTone* to capture sentiment at the environmental, social, and governance levels, respectively. In addition, we examine the relation between the dependent variables and ESG narrative sentiment over the full sample period (2017–2024), exploiting the availability of ESG tone measures even in years when ESG credit indicators are not disclosed.

the informativeness of S&P's proprietary ESG credit indicators against both ESG narrative tone in credit rating reports and external ESG ratings. This framework enables us to assess whether the quantitative ESG credit indicators exhibit stronger, weaker, or complementary associations with the outcome variables relative to ESG textual sentiment and LSEG ESG scores.

4 Main results

4.1 Descriptives and correlations

Table 1 reports summary statistics for the variables used throughout the paper. Panel A presents the ESG-related content of S&P credit rating reports. The ordinal ESG credit indicators are coded on a 1–5 scale, with higher values reflecting more negative credit-relevant ESG assessments. For ease of interpretation in subsequent analyses, we invert these indicators to construct an average score, *ESGScore*, as well as pillar-level scores *EScore*, *SScore*, and *GScore*. The inverted scores cluster tightly around −2: the means of *ESGScore*, *EScore*, *SScore*, and *GScore* are −2.122, −2.231, −2.142, and −1.993, respectively. The 25th percentile equals −2.333 for *ESGScore* and −2 for each of the three pillars, indicating that severe ESG concerns are relatively rare and that, on average, firms exhibit neutral to mildly adverse ESG profiles.

Text-based measures derived from rating-report narratives exhibit substantial dispersion. The composite sentiment measure, *ESGTone*, has a mean of −0.303 and a large standard deviation of 33.867, indicating considerable cross-sectional variation in the tone of ESG discussions and, on average, slightly negative sentiment.[15] The pillar-level tone measures show a similar pattern: the means of *ETone* and *STone* are −2.028 and −1.851, respectively,

[15] The 25th percentile, median, and 75th percentile of *ESGTone* are all zero because only about 57% of reports in our sample contain a dedicated ESG section; reports without an ESG section are coded as zero, mechanically concentrating the middle of the distribution at zero. Conditioning on reports with an ESG section, the mean (s.d.) of *ESGTone* is −0.533 (44.935), indicating slightly negative sentiment with substantial variation (untabulated).

whereas the mean of *GTone* is 5.681, suggesting that environmental and social discussions are more negative on average, while governance discussions are relatively more positive.

Regarding the volume of ESG narrative, *ESG_Prop* (the percentage of sentences in the ESG section relative to the full report) has a mean of 4.327 (s.d. 5.688), and *ESG_Length* (the natural logarithm of the number of sentences in the ESG section) has a mean of 0.773 (s.d. 0.903).[16]

Panel B reports bond-level variables. Measures of the secondary-market information environment exhibit substantial cross-sectional variation. Bid–ask spread volatility, *Spread_Vol (t+1)*, has a mean of 0.057 (s.d. 0.099), indicating considerable heterogeneity in the stability of trading costs across securities. Volatility in quoted G-spreads, *GSpread_Vol (t+1)*, averages 0.433 (s.d. 0.663), further reflecting pronounced variation in credit-spread dynamics across bonds. The average effective daily bid–ask spread, *Avg_BidAsk (t+1)*, is 0.506 (s.d. 0.522), while the median effective daily bid–ask spread, *Med_BidAsk (t+1)*, is 0.393 (s.d. 0.654), suggesting significant dispersion in trading frictions across the bond sample. Turning to bond -market responsiveness, the magnitude of price responses around credit rating report releases is captured by absolute cumulative abnormal returns. *AbsCAR* $[-3, 3]$ average 0.654 (s.d. 0.902), indicating economically meaningful dispersion in the intensity of bond-price reactions. In contrast, signed cumulative abnormal returns are centered near zero: *CAR* $[-3, 3]$ has a mean of 0.001 (s.d. 1.003).

Panel C reports descriptive statistics for the key dependent variables at the report level. The contemporaneous S&P credit rating (*SP_Rating*) has a mean of 12.305 (s.d. 3.031), while the one-year-ahead rating, *SP_Rating (t+1)*, is slightly lower on average (mean 12.295; s.d. 3.079). Panel D reports firm-level control variables. Approximately 60% of firms in the sample received ESG credit indicator coverage at least once in their credit rating reports between

[16] The average volume of ESG narrative is relatively low because reports without a dedicated ESG section are assigned zeros (approximately 43% of the sample). Among reports that include an ESG section, the ESG section accounts for about 7.6% of the full report, and the natural logarithm of the number of sentences in the ESG section has a mean of 1.361 (untabulated).

September 2021 and August 2023, with *ESG_Covered* having a mean of 0.600. *Leverage* has a mean of 0.329. Average firm size, proxied by *MktCap*, is 9.263, consistent with S&P coverage concentrating on larger and more publicly visible firms. Regarding textual sentiment, the overall report tone (*Report_Tone*) averages 16.837 (s.d. 14.500), whereas *ESGTone* is lower on average (mean −0.303, s.d. 33.867) and substantially more dispersed, indicating that sentiment in the ESG discussion is both more negative and more variable than in the report as a whole.

Panel E of Table 1 reports the correlations between S&P ESG credit indicators and ESG narrative tone. The correlations between pillar-level scores and the corresponding tone measures are positive and moderate in magnitude (0.360 for *EScore* and *ETone*, 0.116 for *SScore* and *STone*, and 0.028 for *GScore* and *GTone*), indicating that more favorable ESG scores tend to be associated with more positive ESG narratives, although the two sets of measures are far from redundant.

Panel E also reports the correlations between S&P ESG credit indicators and third-party LSEG pillar-level ESG scores. The pairwise correlations are economically small: 0.036 between *LSEG_EScore* and *EScore*, 0.050 between *LSEG_SScore* and *SScore*, and −0.185 between *LSEG_GScore* and *GScore*. The low magnitudes indicate that the ESG credit indicators in S&P credit rating reports—which are explicitly tied to creditworthiness—differ substantially from LSEG's ESG scores, which are designed to capture broader firm-level ESG performance. This divergence is consistent with methodological differences among providers and, as noted in prior literature, with the possibility that issuer-paid credit analysts incorporate private information not available to investor-oriented rating agencies (Huang et al., 2023).

4.2 Who receives S&P ESG credit indicators?

To understand which firms are more likely to have ESG credit indicators published in S&P credit rating reports, we estimate logit specifications in which the dependent variable equals one if at least one of the firm's credit rating reports issued between September 2021 and August 2023 contains ESG credit indicators (*ESG_Covered*).

Panel A of Table 2 shows that larger firms are significantly more likely to receive ESG credit indicator coverage. Loss-making firms are less likely to be covered, while leverage is positively associated with coverage, consistent with greater creditor salience prompting heightened attention to ESG-related credit risk. Firms with higher market-to-book ratios are less likely to be covered.

Because these results indicate that firm fundamentals are systematically related to S&P's ESG credit indicator coverage decisions, we employ an entropy-balanced sample in the subsequent DiD analyses. Panel B.1 reports group means for firms with and without ESG credit indicator coverage and the corresponding differences. Prior to matching, we observe statistically significant differences across all firm-fundamental covariates. Panel B.2 reports the post-matching means, which exhibit no statistically significant differences between the two groups, indicating that entropy balancing achieves close covariate balance.

4.3 Informational value of ESG credit indicators

The secondary bond market provides a setting well-suited to assessing the informational value of S&P's ESG credit indicators. Table 3 relies on bond transaction data to construct the average and median effective daily relative bid–ask spreads (*Avg_BidAsk (t+1)* and *Med_BidAsk (t+1)*), which capture trading frictions. Table 4 uses quoted bond prices to construct the standard deviation of the daily quoted bid–ask spread (*Spread_Vol (t+1)*), which proxies for uncertainty in trading costs, and the standard deviation of the daily quoted G-spread (*GSpread_Vol (t+1)*), which captures volatility in credit spreads. Using bond–level panel data, we estimate DiD specifications around the introduction and subsequent removal of ESG credit indicators. The analysis is conducted on an entropy-balanced matched sample of firms with and without ESG credit indicator coverage.

To assess the validity of the parallel trends assumption underlying our DiD design, we further examine the dynamic effects of ESG credit indicator adoption by estimating an event-time specification in which treatment effects are allowed to vary by year relative to adoption. Specifically, we include separate interaction terms for each of the two years before and after the introduction of ESG credit indicators. Figure 2, Panels A and B, plots the year-specific treatment-effect coefficients for the bond-market information environment along with their 95% confidence intervals. The estimated coefficients show no statistically or economically significant differences between ESG-covered and non-covered bonds in the pre-adoption period, providing support for the parallel trends assumption. In contrast, the post-adoption coefficients indicate a significant decline in effective bid–ask spread and quoted bid–ask spread volatility for ESG-covered bonds relative to non-covered bonds, consistent with greater stability in trading costs and an improved secondary-bond-market liquidity and information environment following the introduction of ESG credit indicators.

Turning to the main DiD results, Table 3, columns (1) and (3) show that the coefficients on *Adopt* × *ESG_Covered* are negative and statistically significant, indicating that following S&P's introduction of ESG credit indicators, ESG-covered bonds experience a relative improvement in their secondary-market liquidity compared with non-covered bonds. Economically, the estimates imply that, relative to non-covered bonds, ESG-covered bonds exhibit a 0.047 lower average effective bid–ask spread and a 0.036 lower median effective bid–ask spread after the introduction of ESG credit indicators. These effects correspond to reductions of approximately 9.3% and 9.2% of the respective sample means for *Avg_BidAsk (t+1)* (0.047/0.506) and *Med_BidAsk (t+1)* (0.036/0.393). By contrast, the interaction terms *Abandon* × *ESG_Covered* in columns (2) and (4) are positive and statistically significant. This indicates that the withdrawal of ESG credit indicators leads to a systematic deterioration in liquidity, as evidenced by an increase in effective bid–ask spreads relative to non-covered bonds. The magnitude of these effects suggests that removing ESG coverage increases the average effective spread by approximately 4.9% (0.025/0.506) and the median effective spread by approximately 9.4% (0.037/0.393) relative to the sample means. Overall, the results suggest an asymmetric but consistent role of ESG credit indicators in the secondary bond market: their introduction is associated with lower information asymmetry and improved trading conditions, while their removal is associated with heightened information asymmetry and worsened trading conditions.

Table 4, columns (1) and (3), show that the coefficients on $Adopt \times ESG\_Covered$ are negative and statistically significant. These estimates indicate that following the introduction of ESG credit indicators, ESG-covered bonds exhibit lower volatility in quoted bid–ask spreads and quoted G-spreads relative to matched non-covered bonds. This pattern is consistent with greater stability in trading costs and credit spreads when ESG credit indicators are available to market participants, reflecting an improved secondary-bond-market information environment. By contrast, the interaction terms $Abandon \times ESG\_Covered$ in columns (2) and (4) are economically small and statistically insignificant. One interpretation is that market participants continue to rely on previously disclosed ESG credit assessments when forming expectations about covered firms, particularly if ESG-related credit risk is perceived to be relatively persistent over short horizons. As a result, the informational advantage for previously covered firms may not immediately dissipate following the removal of the indicators. More generally, the absence of strong reversal effects suggests that ESG credit indicators may have lasting informational value. Taken together, the results indicate that ESG credit indicators are associated with greater stability in the secondary bond market following their introduction, while the effects of their removal are more muted, reinforcing the view that prominently disclosed, credit-oriented ESG information enhances the bond-market information environment in a persistent manner.

We next examine whether the introduction and subsequent withdrawal of ESG credit indicators affect the magnitude of bond -market responsiveness. Figure 3 displays the event-time treatment-effect coefficients for the absolute value of cumulative abnormal returns, with 95% confidence intervals. The pre-adoption coefficients are economically negligible and statistically indistinguishable from zero, supporting the parallel-trends assumption. In the post-adoption period, however, the coefficients are positive and significant, indicating that ESG-covered bonds experience stronger market reactions to rating reports compared to non-covered bonds.

Table 5 reports DiD estimates using the absolute value of cumulative abnormal bond returns as the dependent variable, measured around the credit rating report filing date ($AbsCAR[-3, 3]$). In column (1), the coefficient on $Adopt \times ESG\_Covered$ is positive and statistically significant, indicating that following the introduction of ESG credit indicators, ESG-covered bonds experience larger absolute price reactions around credit rating report releases relative to matched non-covered bonds. This result suggests that the availability of ESG credit indicators is associated with stronger bond-market responses to rating reports, consistent with these indicators enhancing the salience and interpretability of credit-relevant ESG information for investors. By contrast, in column (2), the coefficient on $Abandon \times ESG\_Covered$ is negative but statistically insignificant. This indicates that the withdrawal of ESG credit indicators is not associated with a statistically distinguishable change in the magnitude of bond -market responsiveness for previously covered bonds over the [-3, 3] event window. Therefore, while the introduction of ESG credit indicators appears to amplify investors' responses to new credit information, the evidence does not show a significant dampening effect following their removal within this shorter event window. Overall, the results suggest that ESG credit indicators sharpen bond -market responsiveness when they are introduced, highlighting their role as a salient and decision-useful summary of ESG-related credit risk.

Table 6 examines bond price reactions around the release of credit rating reports by relating cumulative abnormal bond returns over the event window $CAR[-3,3]$ to the aggregate ESG credit indicator (*ESGScore*).[17] In column (1), the coefficient on *ESGScore* is positive and statistically significant, indicating that more favorable ESG credit indicators are associated with higher bond-market returns around the report issuance date. Economically, a one-unit increase in *ESGScore* is associated with an approximately 0.37 percentage-point increase in $CAR[-3,3]$. In column (2), *ESGTone* enters positively and is statistically significant, suggesting that the sentiment of the ESG narrative contains incremental value-relevant information for bond investors. Column (3) further augments the specification by including third-party LSEG ESG scores. *LSEG_ESGScore* is positive and statistically significant, indicating that external ESG ratings also convey information that investors incorporate around rating-report releases. Importantly, *ESGScore* remains positive and statistically significant when jointly included with *ESGTone* and *LSEG_ESGScore*, indicating that S&P's ESG credit indicators provide incremental information beyond both ESG narrative tone and widely used third-party ESG ratings. Overall, the evidence indicates that S&P's ESG credit indicators convey incremental, credit-relevant information that is reflected in bond price reactions around credit rating report releases.

Table 6 columns (4) through (6) extends the baseline bond-market reaction analysis by allowing the effect of ESG credit indicators to vary with contemporaneous changes in S&P credit ratings. Specifically, we augment the specification by including the interaction between the aggregate ESG credit indicator and the change in credit ratings, $ESGScore \times \Delta SP\_Rating$. This interaction is motivated by the concern that market reactions attributed to ESG credit indicators may be mechanically driven by, or conditional on, rating changes released at the same time. If ESG credit indicators merely proxy for the information contained in rating actions, their association with bond price reactions should be attenuated or concentrated

[17] The number of observations differs across tables due to differences in data sources and sample construction. Table 4, Table 5, and Table 6 rely on quoted bond price data from Datastream, whereas Table 3 uses bond transaction data from TRACE. In addition, the regressions in Table 6 are restricted to periods in which ESG credit indicators are disclosed, resulting in fewer observations than those in Table 5.

when ratings change.

Across all specifications in columns (4) through (6), the interaction term *ESGScore* $\times$ Δ*SP_Rating* is economically small and statistically insignificant. This result indicates that the association between ESG credit indicators and bond price reactions does not depend on contemporaneous rating changes. In other words, the market response to ESG credit indicators is not confined to, nor amplified by, rating upgrades or downgrades. Consistent with the baseline results, the coefficient on *ESGScore* remains positive and statistically significant across all specifications. The estimated association is robust to the inclusion of controls for ESG narrative tone (column (5)) and third-party LSEG ESG scores (column (6)). Economically, a one-unit increase in *ESGScore* is associated with an increase of approximately 0.24 to 0.37 percentage points in $CAR[-3,3]$. The persistence of the *ESGScore* effect suggests that ESG credit indicators convey incremental, credit-relevant information that is distinct from both rating changes and other ESG disclosures. Taken together, the results indicate that ESG credit indicators influence bond price reactions independently of contemporaneous rating actions. This evidence suggests that investors treat ESG credit indicators as a separate informational signal rather than merely as a byproduct of rating changes, reinforcing the interpretation that numeric ESG credit indicators provide incremental and decision-useful information beyond traditional credit rating announcements.

4.4 Relevance of ESG credit indicators to credit ratings

We next examine whether ESG credit indicators are related to S&P's credit ratings. This analysis is important because the indicators are designed to communicate the credit impact of ESG factors, but they are not intended to mechanically determine rating outcomes. Thus, a systematic association between the indicators and credit ratings would indicate that the indicators capture ESG related risk dimensions that are embedded in S&P's broader credit assessment. Moreover, because many ESG related risks are persistent and forward-looking, we examine both contemporaneous and next-year ratings.

Table 7 examines whether S&P ESG credit indicators are incorporated into issuers' contemporaneous and future credit ratings by estimating Equation (3). The dependent variable is defined as either the current S&P credit rating (*SP_Rating*) or the one-year-ahead rating (*SP_Rating (t+1)*), and the regressions relate these outcomes to the aggregate ESG credit indicator (*ESGScore*) over the 2021–2023 period, during which ESG credit indicators were disclosed. Across all specifications, *ESGScore* is positive and statistically significant at the 1% level for both contemporaneous and next-year ratings. The estimated coefficients range from 1.495 to 1.642, implying that a one-unit improvement in the aggregate ESG credit indicator is associated with approximately a 1.57-notch higher S&P credit rating. By contrast, *ESGTone* is economically small and statistically insignificant. These patterns indicate that the quantitative ESG credit indicators are substantially more informative for both current and future S&P ratings than the tone of ESG narratives.

Columns (3) and (6) compare the incremental association of third-party LSEG ESG scores with that of S&P ESG credit indicators and ESG narrative tone. *LSEG_ESGScore* is positively and significantly associated with both current and future credit ratings in these specifications, suggesting that external ESG ratings contain information that S&P incorporates into its ratings. Importantly, both *ESGScore* and *LSEG_ESGScore* remain statistically significant when included jointly, although the economic magnitude of *ESGScore* is substantially larger. A one-standard-deviation increase in *ESGScore* is associated with a 0.53-notch increase in contemporaneous ratings (1.642×0.324) and a 0.51-notch increase in next-year ratings (1.569×0.324). In comparison, a one-standard-deviation increase in *LSEG_ESGScore* is associated with a 0.29-notch increase in contemporaneous ratings (0.119×2.253) and a 0.25-notch increase in next-year ratings (0.113×2.253). Thus, on a standardized basis, the economic magnitude of the association for *ESGScore* is approximately 80% larger for contemporaneous ratings and 104% larger for next-year ratings, relative to that of *LSEG_ESGScore*.

Overall, these findings indicate that the proprietary ESG credit indicators embedded in S&P

credit rating reports are strongly incorporated into both current and future credit ratings and provide more rating-relevant information than either qualitative ESG narrative tone or external ESG ratings. At the same time, LSEG ESG scores also exhibit a positive association with S&P ratings, suggesting that they capture some of the underlying ESG risk dimensions, albeit less tightly than S&P's own credit-embedded ESG indicators.

4.5 Predictive content of ESG credit indicators

Credit rating reports contain forward-looking information relevant to default prediction and credit risk assessment, longstanding focal points in corporate finance and risk management (Altman, 1968; Beaver, 1966; Ohlson, 1980). S&P's ESG credit indicators may enhance this forward-looking content by systematically summarizing ESG-related risks that are expected to affect firms' future operating performance and cash-flow stability in a structured and comparable manner. Table 8 evaluates whether S&P ESG credit indicators are predictive of subsequent firm performance. We estimate Equation (3), replacing the dependent variable with next-year return on assets (*ROA (t+1)*), EBITDA margin (*EBITDA_Margin (t+1)*), and earnings volatility (*Earnings_Vol*).

Columns (1)–(3) show that *ESGScore* is not significantly related to next-year ROA. The estimated coefficients are small and statistically insignificant across specifications, suggesting that ESG credit indicators are not systematically associated with short-term accounting profitability. This finding is consistent with the view that ESG credit indicators are primarily designed to capture credit-relevant risk exposures rather than to predict near-term levels of overall operating profitability. Columns (4)–(6) present results for EBITDA margin, a measure of operating efficiency. In contrast to ROA, *ESGScore* is positively and statistically significantly associated with future EBITDA margins in columns (4) and (5). More favorable ESG credit indicators are associated with higher operating margins in the subsequent year, indicating that firms assessed as having lower ESG-related credit risk tend to exhibit stronger operating efficiency. This pattern is consistent with ESG-related risks affecting cost structures, operational efficiency, or exposure to operational disruptions, which are more directly reflected in operating margins than in aggregate profitability measures such as ROA. However, when third-party LSEG ESG scores are included in column (6), the association between *ESGScore* and EBITDA margin becomes statistically insignificant. Notably, *LSEG_ESGScore* enters negatively and significantly, suggesting that external ESG ratings may capture different dimensions of ESG performance — potentially more aligned with long-term sustainability or stakeholder engagement — that do not translate into near-term operating margins. Alternatively, this negative coefficient may reflect measurement differences or noise in external scores that absorb part of the signal captured by S&P's credit-oriented indicators.

Columns (7)–(9) examine earnings volatility as a measure of firm risk. The coefficients on *ESGScore* are negative and statistically significant across all specifications, indicating that more favorable ESG credit indicators are associated with lower future earnings volatility. This result suggests that ESG credit indicators capture dimensions of risk that translate into more stable earnings outcomes, consistent with their intended role as forward-looking measures of credit-relevant ESG risk.

Taken together, the results indicate that ESG credit indicators are more strongly related to future firm risk than to short-term profitability. While they do not predict next-year ROA, they are associated with higher future operating margins and, more robustly, with lower earnings volatility. These findings suggest that ESG credit indicators primarily reflect firms' exposure to ESG-related risks that affect the stability and resilience of cash flows rather than immediate profitability, reinforcing their relevance for credit risk assessment.

4.6 Interaction between ESG credit indicators and ESG narrative content

S&P ESG credit indicators, embedded as pillar-level numeric scores in issuer rating reports, provide a structured and comparable summary of ESG-related credit risk. Their adoption may reduce the need for extensive ESG narratives in some cases, as part of the ESG assessment is communicated numerically, thereby lowering disclosure volume at the extensive margin. At the same time, more adverse ESG indicators may prompt analysts to elaborate on the underlying drivers of ESG risk, increasing ESG-related narrative intensity at the intensive margin. These considerations motivate tests of (i) how the adoption and subsequent withdrawal of ESG credit indicators affect the ESG narratives in credit rating reports, and (ii) how the level of ESG credit indicators is related cross-sectionally to the ESG-related narrative content. Accordingly, we examine whether S&P altered the channel through which ESG information is conveyed in credit rating reports and how ESG narrative content interacts with the presence and level of ESG credit indicators.

To examine whether ESG credit indicators complement or substitute for ESG narrative disclosures in S&P credit rating reports, we estimate Equations (2a) and (2b) at the report level, replacing the dependent variable with measures of the volume and qualitative characteristics of the ESG section within each credit rating report. Our proxies for the volume of ESG narrative content include the proportion of sentences in the ESG section relative to the full report (*ESG_Prop*) and the natural logarithm of the total number of sentences in the ESG section (*ESG_Length*). Our proxies for the characteristics of the ESG section include the specificity of ESG-related content in the ESG section (*ESG_Spec*) and the prevalence of forward-looking ESG statements within the ESG section (*ESG_FLS*). ESG-related content is identified using a finance-domain BERT-based classifier (FinBERT-ESG), which is fine-tuned on manually annotated sentences from ESG and annual reports and assigns each sentence to one of four categories: environmental, social, governance, or none. We define

ESG disclosure as the subset of sentences in the ESG section classified into the environmental, social, or governance categories. Detailed variable definitions are provided in Appendix 2. In all specifications, we include firm fixed effects (*Firm FE*) and year fixed effects (*Year FE*) to control for time-invariant firm heterogeneity and common time trends.

To evaluate the validity of the parallel trends assumption, we estimate a dynamic DiD specification for ESG narrative content. Panels A and B of Figure 4 plot the year-specific treatment-effect coefficients for the proportion and length of ESG-related content together with their 95% confidence intervals. The estimated coefficients in the pre-adoption period are economically small and statistically indistinguishable from zero, indicating no differential trends in ESG narrative intensity between ESG-covered and non-covered firms prior to the introduction of ESG credit indicators. In the post-adoption period, the coefficients turn significantly negative, reflecting a reduction in the share of ESG-related sentences in ESG-covered reports after the indicators are introduced, consistent with substitution away from narrative disclosure when numeric ESG credit indicators are displayed.

Using DiD specifications around the adoption and subsequent removal of ESG credit indicators, Table 9 shows that the coefficients on $Adopt \times ESG\_Covered$ in columns (1), (3), and (7) are negative and statistically significant. Thus, when ESG credit indicators are displayed, both the volume of the ESG section (*ESG_Prop* and *ESG_Length*) and the prevalence of forward-looking ESG-related language within the ESG section (*ESG_FLS*) decline for ESG-covered firms relative to matched non-covered firms, consistent with substitution away from narrative discussion when a numeric summary is available. This pattern is also consistent with the indicators conveying forward-looking information that partially substitutes for forward-looking ESG statements in the ESG section. For the removal event (columns (2), (4), (6), and (8)), the interaction terms $Abandon \times ESG\_Covered$ are positive but statistically insignificant. Overall, we find clear evidence that the introduction of ESG credit indicators is associated with a reduction in ESG narrative volume and in forward-looking

ESG statements, but weaker and less conclusive evidence that their discontinuation leads to a systematic expansion of ESG narrative disclosure.

To examine the association between ESG credit indicators and ESG narrative disclosures, we estimate Equation 3 using measures of the volume and characteristics of ESG narrative content as the dependent variables.[18] Table 10 presents evidence on the cross-sectional association between the level of ESG credit indicators and ESG narrative content during the 2021-2023 scoring regime. Columns (1) and (2) show that the aggregate indicator, *ESGScore*, is negatively and statistically significantly related to *ESG_Prop* and *ESG_Length*, indicating that more adverse ESG assessments are associated with more extensive ESG narrative discussion. In columns (3) and (4), the coefficients on *ESGScore* are negative but statistically insignificant, suggesting that the level of ESG credit indicators is not systematically related to the specificity of ESG content or the prevalence of forward-looking language in the ESG narrative. Taken together, these results indicate that, within the scoring regime, S&P expands ESG-related narrative when assessed ESG credit risk is higher, consistent with complementarity between adverse numeric assessments and explanatory text at the intensive margin.

Overall, the evidence suggests substitution at the extensive margin—introduction of ESG credit indicators reduces the volume of ESG narrative—but complementarity at the intensive margin, whereby more adverse ESG credit assessments are accompanied by richer ESG discussion.

[18]We also extend this analysis to entire credit rating reports. Specifically, we apply the FinBERT-ESG model to the full text to compute the proportion of ESG-related sentences in the whole report, and replace the ESG-section–based measures accordingly. The results are qualitatively similar and are reported in the Online Appendix.

5 Conclusion

This paper contributes to the debate over the usefulness of numeric ESG credit indicators relative to qualitative ESG narratives in enhancing the informativeness of credit rating reports. Exploiting the introduction (2021) and subsequent removal (2023) of S&P ESG credit indicators, we examine how their presence affects secondary bond-market outcomes, assess their relevance for current and future credit ratings, evaluate whether they possess predictive content for subsequent firm financial performance, and analyze how their display interacts with the volume and structure of ESG narrative disclosure.

Four main conclusions emerge. First, the adoption of ESG credit indicators improves bond-market liquidity, consistent with reduced trading frictions relative to narrative-only disclosures. The indicators also amplify investors' reactions to new credit information, suggesting that numeric ESG credit indicators enhance the salience and interpretability of credit-relevant ESG signals for market participants. Moreover, more favorable indicators are associated with higher cumulative abnormal bond returns around credit rating report releases, suggesting that investors positively update bond values in response to better ESG assessments. Second, more adverse ESG credit indicators are associated with lower current and next-year credit rating levels, indicating that ESG risk is incorporated into credit assessments. Third, ESG credit indicators have both informational and predictive value: they are significant predictors of future firm financial performance, with stronger predictive power than ESG narrative tone or third-party ESG scores. Fourth, ESG credit indicators and ESG narrative disclosure operate as substitutable channels: when indicators are displayed, the volume and forward-looking content of ESG discussion decline. Within the scoring regime, however, more adverse ESG indicators are accompanied by greater ESG-related text, indicating that narrative explanation increases when ESG risk is more salient.

These findings carry several important implications. Our evidence is drawn from S&P's scoring regime and thus speaks most directly to credit-oriented ESG metrics in the rating-report context. For CRAs, presenting both ESG credit indicators and qualitative ESG analysis yields more transparent and decision-useful ESG communication than relying on either modality alone. For regulators, ESG credit indicators appear demonstrably informative: they are incorporated into both current and future credit ratings and exhibit predictive power for subsequent firm financial performance. In addition, the inclusion of ESG credit indicators in credit rating reports reduces bond-market frictions and enhances price discovery, thereby complementing narrative disclosure. Accordingly, policies that promote the systematic inclusion of credit-oriented ESG indicators could strengthen the informational value of credit rating reports, improve transparency regarding ESG-related financial risks, enhance market efficiency, and support broader environmental policy objectives.

Future work could examine heterogeneity across industries and geographies, alternative ESG taxonomies, and the persistence of the documented effects as scoring frameworks evolve.

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Appendix 1. Anecdotal evidence on ESG credit indicators

This appendix presents verbatim statements from news articles and market commentary concerning ESG credit indicators. The excerpts illustrate views expressed by market participants and commentators regarding the usefulness of ESG credit indicators and the implications of their removal from credit rating reports. All quotations are reproduced as they appear in the original sources.

A. Support for ESG credit indicators

A1. Source: Ahren Lester, "Surprise as S&P drop ESG scores from credit ratings," *Environmental Finance*, August 9, 2023.

> " Although debt investors rarely base their creditworthiness assessments entirely on the summative credit rating of an issuer, these ubiquitous credit scores have often proven useful first ports-of-call for the analysis – serving as a valuable initial screening, in some cases, and providing a useful indicator for where and when to dig deeper into credit details.
>
> ESG indicators in credit reports could and perhaps should play a similar role as a first – but not final – part of the process for investors. "

> " Nawar Alsaadi – chief executive at ESG advisory firm Kanata Advisors – says that the decision could be counter-productive from a transparency standpoint...
>
> ..."If S&P is still integrating ESG information in their creditworthiness determinations, eliminating the ratings decreases the transparency of how ESG data is being used to impact S&P credit assessments," he says.
>
> Although the actual credit ratings applied to issuers – such as the long-term ratings, which range from the highest 'AAA' rating to 'D' – are only high-level indicators, they remain useful from a transparency perspective.
>
> As a result, Alsaadi argues that: "If narratives were sufficient to help investors appreciate credit risk, why doesn't S&P drop its letter-based credit ratings altogether and provide narrative ratings across the board for ESG and non-ESG risks?" "

> " "Eliminating the ratings decreases the transparency of how ESG data is being used to impact S&P credit assessments" - Nawar Alsaadi, Kanata Advisors "

A2. Source: Dan Byrne, "S&P ESG rating story exposes serious vulnerabilities," *Corporate*

Governance Institute, 2023.

> "Investors and other stakeholders often depend on numerical metrics for proper awareness. They contextualise. They establish a base from which to elaborate on more complex opinions. Most of all, they often add weight and importance to decision-making."

B. Criticism of ESG credit indicators

B1. Source: Ahren Lester, "Surprise as S&P drop ESG scores from credit ratings," *Environmental Finance*, August 9, 2023.

> "A source with knowledge of the decision-making process tells Environmental Finance the move followed feedback from market participants that the scores – which were meant to summarise and complement the underlying ESG analysis – were not proving the more effective way of expressing ESG factors in the credit rating process."

> "Whilst credit ratings are closely regulated, other areas where firms such as S&P are also integrating ESG scores are not under the same scrutiny – for example, second-party opinions (SPOs)."

B2. Source: Mark Segal, "S&P Removes ESG Indicators from Credit Rating Reports," *ESG Today*, August 9, 2023.

> "Last year, S&P Global was subject to an investigation by Republican attorneys general in several U.S. states, launched by Missouri Attorney General Eric Schmitt and forming part of a broader anti-ESG campaign, alleging that the company's ESG evaluations, including its ESG credit indicators, were politicizing financial analysis."

B3. Source: Patrick Temple-West, "S&P drops ESG scores from debt ratings amid scrutiny," *Financial Times*, August 8, 2023.

> "Andy Brenner, head of international fixed income at Natalliance Securities, said he agreed with S&P's decision to back away from ESG scores. "[ESG] is very hard to measure. I think it's an overrated concept," he said."

B4. Source: "Paxton Launches Investigation into S&P Global's Use of ESG Factors in Credit Ratings, Potentially Violating Consumer Protection Laws," *Office of the Attorney*

General of Texas, September 28, 2022.

> " S&P's published ESG credit indicators, ESG scores, and ESG evaluations appear to politicize what should be a purely financial decision and may deceptively confound the distinction between subjective opinions and objective financial facts. "

B5. Source: "S&P eliminates ESG scores from credit ratings," *Ballotpedia*, August 15, 2023.

> " ESG scoring frameworks within credit ratings don't work, according to Patrick Welch, chief ESG and ratings policy officer at Kroll Bond Rating Agency, a smaller rival of S&P.
>
> With a 1-to-5 scale "you're putting one scoring system – an ESG one – inside another scoring system, which is the credit rating," Welch said in an interview. "It raises confusion – are you talking about financial risk to the company, or also its impact" on society and the environment? "

C. Explanations for the removal of ESG credit indicators

C1. Source: "Surprise as S&P drop ESG scores from credit ratings," *Environmental Finance*, August 9, 2023.

> " Alsaadi – who was previously an ESG-focused portfolio manager – tells Environmental Finance it is possible that the move was, at least in part, driven by the anti-ESG rhetoric growing in some markets, such as the US. "

> " Another market expert wondered whether the decision by S&P to drop the ESG credit indicator was a "retreat" to the "relative safety" of unregulated markets for their ESG-related scores and analysis. "

C2. Source: Patrick Temple-West, "S&P drops ESG scores from debt ratings amid scrutiny," *Financial Times*, August 8, 2023.

> " S&P is influential, with debt ratings that can affect a company's borrowing cost. As Republicans target Wall Street's use of ESG more broadly, conservative state attorneys-general last year opened an investigation into S&P's use of the factors. "

> " Tom Lyon, a professor at University of Michigan's business school who has

studied ESG ratings, said the S&P move was "just the latest example of a company crumpling in the face of these Republican attacks". "

" By dropping the ESG ratings now, maybe S&P is saying "the ratings really are not that useful," said David F. Larcker, a professor at Stanford's graduate school of business. "Or maybe they are responding to pressure from attorneys-general and other people who are anti-ESG." "

C3. Source: Dan Byrne, "S&P ESG rating story exposes serious vulnerabilities," *Corporate Governance Institute*, 2023.

" S&P won't say for definite, but media and critics have flagged one reason in particular: ESG backlash.

It's heavily prominent in the United States. The Republican Party is solidifying around an anti-ESG stance as one of its main arguments, fuelled by leaders such as Texas and Florida governors Gregg Abbott and Ron DeSantis.

In their eyes, ESG is "woke" and an infringement on the free-market and maximum shareholder return. "

" Last year, S&P became the subject of a Republican-led investigation precisely because of its ESG scoring system...Meanwhile, critics appear clear that S&P's move is an obvious response to the right-wing backlash. "

C4. Source: James Hannay, "S&P Global Ratings to stop publishing ESG credit indicators," *Sustainability News*, August 11, 2023.

" "...we are no longer publishing new ESG credit indicators in our reports or updating outstanding ESG credit indicators...," the S&P noted in a press release.

The news comes at a time when there has been a growing trend among companies to adopt ESG reporting standards. This is due to a number of factors, including increasing investor demand for ESG information, growing regulatory pressure, and a desire to improve corporate reputation. "

C5. Source: Dan Byrne, "S&P ESG rating story exposes serious vulnerabilities," *Corporate Governance Institute*, 2023.

" Abandoning its only numerical rating in ESG suggests S&P isn't confident that it adds any weight or simply wants to be more subtle in its ESG approach.

Maybe both. ”

C6. Source: “Paxton Launches Investigation into S&P Global’s Use of ESG Factors in Credit Ratings, Potentially Violating Consumer Protection Laws,” *Office of the Attorney General of Texas*, September 28, 2022.

> “ Attorney General Paxton joined a Missouri-led multistate investigation into S&P Global Inc. for potential violations of consumer protection laws...
>
> ...based upon alleged consumer fraud and deceptive trade practices.
>
> “Too many consumers and investors have been hurt by the woke ESG movement’s obsession with radical social change and willingness to ignore the law,” said Attorney General Paxton. “We’re investigating S&P Global to find out if they’ve engaged in the types of destructive, illegal business practices that are so pervasive in the ESG movement...” ”

C7. Source: “S&P eliminates ESG scores from credit ratings,” *Ballotpedia*, August 15, 2023.

> “ S&P Global has decided to eliminate the numerical ESG score from its credit ratings in response to investor concerns: S&P Global Inc. will no longer publish ESG scores along with its credit ratings, as the company adjusts its approach in response to investor feedback.
>
> The update, which took place on Aug. 4, was triggered by expressions of confusion from investors who use S&P’s corporate credit ratings, according to a person close to the process who asked not to be identified discussing feedback that hasn’t been made public...
>
> ...The development comes as ratings providers try to navigate a changing landscape in which there’s little consensus on how to assess the long-term financial impact of environmental, social and governance factors on issuers...
>
> ...S&P’s efforts to introduce an ESG scale to inform its debt ratings weren’t universally understood by investors, the person familiar with the process said. ”

Appendix 2. Variable definitions

Variable	**Definition**	**Source**
Panel A: Credit rating report variables		
EScore	The inverted form of the environmental credit indicator published in the S&P credit rating report, recalibrated so that higher values indicate superior environmental performance.	S&P Capital IQ RatingXpress
SScore	The inverted form of the social credit indicator published in the S&P credit rating report, recalibrated so that higher values indicate superior social performance.	S&P Capital IQ RatingXpress
GScore	The inverted form of the governance credit indicator published in the S&P credit rating report, recalibrated so that higher values indicate superior governance performance.	S&P Capital IQ RatingXpress
ESGScore	The average of *EScore*, *SScore*, and *GScore*.	S&P Capital IQ RatingXpress
ESGTone	The tone of ESG-related sentences in the S&P credit rating report's ESG section. The tone is calculated as the difference between the number of positive and negative sentences (classified by FinBERT) relative to the total number of sentences in percentage.	S&P Capital IQ RatingXpress
ETone	The tone of environment-related sentences in the S&P credit rating report's ESG section.	S&P Capital IQ RatingXpress
STone	The tone of social-related sentences in the S&P credit rating report's ESG section.	S&P Capital IQ RatingXpress
GTone	The tone of governance-related sentences in the S&P credit rating report's ESG section.	S&P Capital IQ RatingXpress
ESG_Prop	The proportion of sentences in the S&P credit rating report's ESG section relative to the total number of sentences in the full report in percentage.	S&P Capital IQ RatingXpress
ESG_Length	The natural logarithm of the number of sentences in the S&P credit rating report's ESG section relative to the total number of sentences in the full report.	S&P Capital IQ RatingXpress
ESG_Spec	The number of words in ESG-related sentences in the S&P credit rating report's ESG section that are named entities (persons, locations, organizations, percentages, monetary values, times, and dates), as identified by named entity recognition (NER), relative to the total number of words in ESG-related sentences in percentage. ESG-related sentences are identified using a finance-domain BERT-based classifier (FinBERT-ESG).	S&P Capital IQ RatingXpress
ESG_FLS	The number of ESG-related sentences in the S&P credit rating report's ESG section that contain at least one forward-looking term, relative to the total number of ESG-related sentences in percentage. Forward-looking terms include "will", "can", "could", "may", "might", "objective", "goal", "shall", "future", "aim", "assume", "commit", "estimate", "foresee", "target", "expect", "anticipate", "believe", "plan", "hope", "intend", "seek", "project", "forecast", and "next/incoming/coming/upcoming/subsequent/following fiscal (year)/month/period/quarter/year". ESG-related sentences are identified using a finance-domain BERT-based classifier (FinBERT-ESG).	S&P Capital IQ RatingXpress
Panel B: Bond-level variables		
Avg_BidAsk	*Avg_BidAsk* is the average daily effective relative bid–ask spread for bond i over the one-year period following the ESG report release date: $$\text{SpreadMean}_{i,T} = \frac{1}{N_{i,T}} \sum_{t=1}^{N_{i,T}} \frac{P_{i,t}^{Ask} - P_{i,t}^{Bid}}{\left(P_{i,t}^{Ask} + P_{i,t}^{Bid}\right)/2}.$$ Here, $P_{i,t}^{Ask}$ is the volume-weighted average price of dealer sales to customers for bond i on day t, and $P_{i,t}^{Bid}$ is the volume-weighted average price of dealer purchases from customers. The measure is computed using only valid bond-day observations for which both bid- and ask-side customer trades are observed and the implied spread is positive.	TRACE
Med_BidAsk	The median value of daily relative bid-ask spreads over the one-year window following the report release date.	TRACE
Spread_Vol	The standard deviation of the daily quoted bid-ask spread for the bond over the one-year period following the report release.	Datastream

Appendix 2. Continued

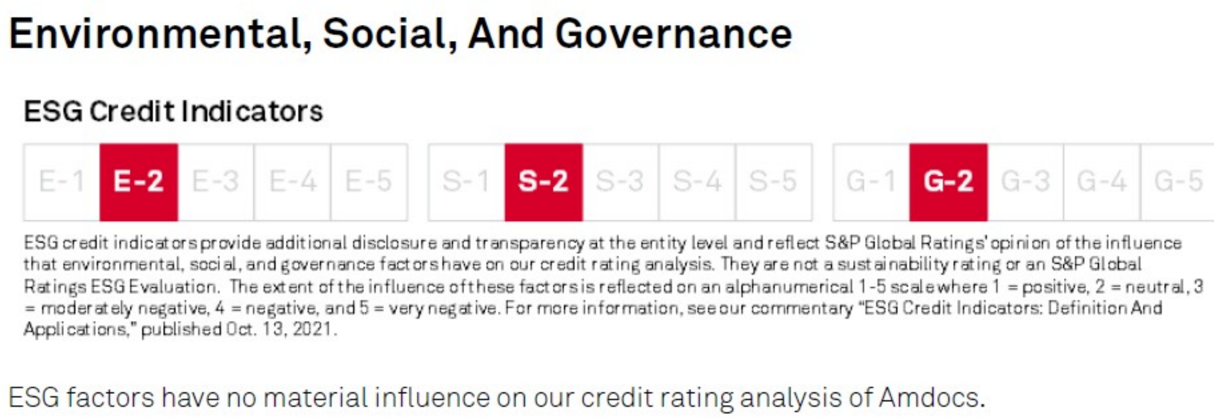
Variable	Definition	Source
GSpread_Vol	The standard deviation of daily G-spreads for a given bond over the one-year period following the report release date. The G-spread is defined as the difference between the bond's yield to maturity and the yield on the government benchmark curve at the equivalent maturity point.	Datastream
AbsCAR [-3, 3]	The absolute value of cumulative abnormal bond return, expressed in percentage terms, measured over the $[-3, +3]$ trading-day window centered on the report release date.	Datastream
CAR [-3, 3]	Cumulative abnormal bond return, expressed in percentage terms, measured over the $[-3, +3]$ trading-day window centered on the report release date. Daily abnormal bond returns are estimated as the residuals from regressing excess bond returns (daily bond return minus the risk-free rate) on the following contemporaneous factor returns: $TERM$ (the return on the 30-year Treasury bond minus the return on the one-month Treasury bill), $DEFAULT$ (the value-weighted return of all corporate bonds in the Datastream database with a maturity greater than 10 years minus the return on the 30-year Treasury bond), $MKTRF$ (the excess return on the market), SMB (the Fama–French size factor), and HML (the Fama–French market-to-book factor).	Datastream
Coupon	The annual coupon rate of the bond (%), expressed as a percentage of the par value.	Datastream/FISD
Coverage_Ratio	Operating income after depreciation plus interest expense scaled by interest expense.	Compustat
Maturity	The natural logarithm of the number of months remaining to maturity, measured at the report release date.	Datastream/FISD
Offering_Amount	The face value of the bond issue at issuance, measured in billions of U.S. dollars.	Datastream/FISD
Panel C: Dependent variables		
SP_Rating	S&P rank based on mapping letter ratings to 1–21 (AAA=1, . . . , C=21).	S&P Capital IQ RatingXpress
ROA	Earnings before interest and taxes divided by total assets.	Compustat
EBITDA_Margin	Earnings before interest, taxes, depreciation, and amortization divided by revenue.	Compustat
Earnings_Vol	The standard deviation of earnings before interest and taxes divided by total assets over the subsequent five fiscal years.	Compustat
Panel D: Independent variables		
Adopt	Dummy equals one if the S&P credit rating report is published after Sept. 2021 and before Aug. 2023; zero if published before Sept. 2021.	
Abandon	Dummy equals one if the S&P credit rating report is published after Aug. 2023; zero if published after Sept. 2021 and before Aug. 2023.	
ESG_Covered	Dummy equals one if S&P published ESG credit indicators in the firm's credit report at least once between Sept. 2021 and Aug. 2023; zero otherwise.	S&P Capital IQ RatingXpress
Panel E: Control variables		
Leverage	Long-term debt divided by total assets.	Compustat
Loss	Dummy equals one if net income is negative; zero otherwise.	Compustat
LSEG_ESGScore	The LSEG ESG score.	LSEG ESG
LSEG_EScore	The LSEG E pillar score measures performance in the categories of resource use, emissions, and innovation categories.	LSEG ESG
LSEG_SScore	The LSEG S pillar score measures performance in the categories of workforce, human rights, community, product responsibility.	LSEG ESG
LSEG_GScore	The LSEG G pillar score measures performance in the categories of management, shareholders, CSR strategy.	LSEG ESG
MktCap	ln(#shares × price) at fiscal year-end preceding the report.	Compustat
Mkt_to_Book	ln(#shares × price/common equity).	Compustat
Report_Length	The natural logarithm of the number of sentences in the S&P credit rating report.	S&P Capital IQ RatingXpress
Report_Tone	The difference between the number of positive and negative sentences (classified by FinBERT) relative to the total number of sentences in S&P credit rating reports in percentage.	S&P Capital IQ RatingXpress
Tangibility	Property, plant, and equipment divided by total assets.	Compustat
ΔSP_Rating	The change in *SP_Rating* from year $t-1$ to year t.	S&P Capital IQ RatingXpress

Appendix 3. Sample selection

Description	No. of Reports	No. of Firms
Credit rating reports published by S&P between January 2017 and July 2024.	44,394	—
Matched with Capital IQ Identifier Linking Query using the report ID, excluding observations with missing firm identifiers (GVKEY).	6,265	1,448
Matched with Compustat data, retaining only observations without missing variables other than *Tangibility*.	5,325	1,197
Subset: Among the 1,897 S&P credit rating reports issued for 952 unique firms between September 2021 and August 2023 (the period during which S&P published ESG credit indicators), reports that include ESG credit indicators.	922	632

Notes: This table outlines the sample selection procedure for the main sample in the empirical analysis. The corresponding numbers of observations for the samples used in additional analyses can be referred to in the relevant tables in the respective sections. The sample period covers January 2017 to July 2024. The "—" indicates that the number of firms is not applicable for the initial collection step.

Figure 1: Examples of ESG credit indicators


Environmental, Social, And Governance

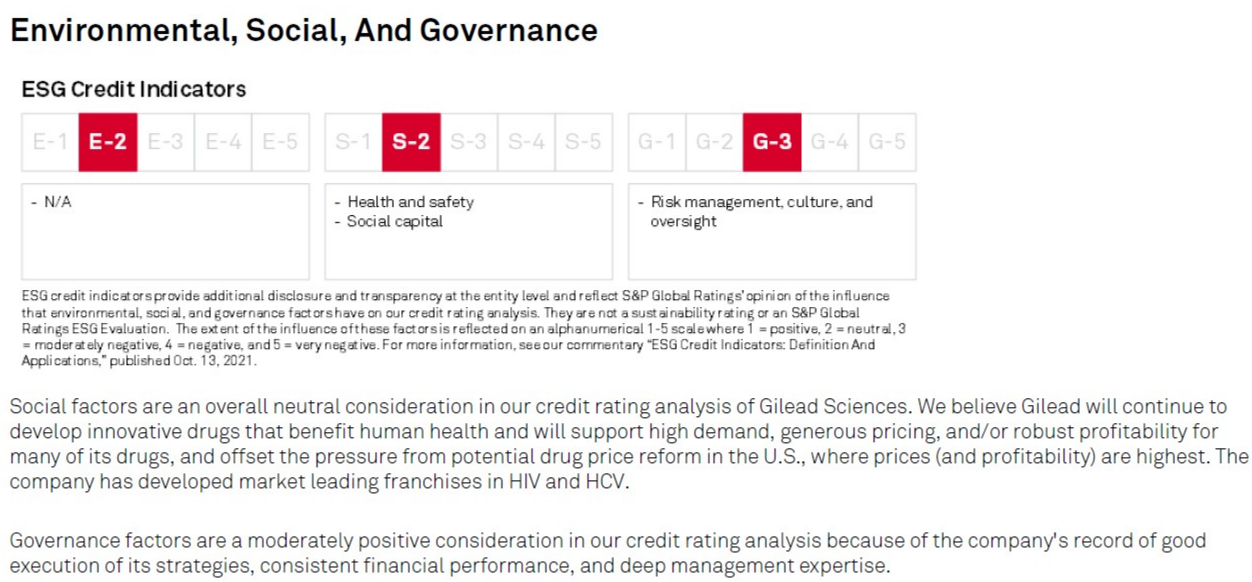
ESG Credit Indicators

E-1	**E-2**	E-3	E-4	E-5	S-1	**S-2**	S-3	S-4	S-5	G-1	**G-2**	G-3	G-4	G-5

ESG credit indicators provide additional disclosure and transparency at the entity level and reflect S&P Global Ratings' opinion of the influence that environmental, social, and governance factors have on our credit rating analysis. They are not a sustainability rating or an S&P Global Ratings ESG Evaluation. The extent of the influence of these factors is reflected on an alphanumerical 1-5 scale where 1 = positive, 2 = neutral, 3 = moderately negative, 4 = negative, and 5 = very negative. For more information, see our commentary "ESG Credit Indicators: Definition And Applications," published Oct. 13, 2021.

ESG factors have no material influence on our credit rating analysis of Amdocs.

Panel A presents an illustrative example of an ESG score adapted from an issuer credit rating report. Source: S&P Capital IQ RatingsXpress (Amdocs Ltd., January 13, 2023).


Environmental, Social, And Governance

ESG Credit Indicators

E-1	**E-2**	E-3	E-4	E-5	S-1	**S-2**	S-3	S-4	S-5	G-1	G-2	**G-3**	G-4	G-5

- N/A	- Health and safety - Social capital	- Risk management, culture, and oversight

ESG credit indicators provide additional disclosure and transparency at the entity level and reflect S&P Global Ratings' opinion of the influence that environmental, social, and governance factors have on our credit rating analysis. They are not a sustainability rating or an S&P Global Ratings ESG Evaluation. The extent of the influence of these factors is reflected on an alphanumerical 1-5 scale where 1 = positive, 2 = neutral, 3 = moderately negative, 4 = negative, and 5 = very negative. For more information, see our commentary "ESG Credit Indicators: Definition And Applications," published Oct. 13, 2021.

Social factors are an overall neutral consideration in our credit rating analysis of Gilead Sciences. We believe Gilead will continue to develop innovative drugs that benefit human health and will support high demand, generous pricing, and/or robust profitability for many of its drugs, and offset the pressure from potential drug price reform in the U.S., where prices (and profitability) are highest. The company has developed market leading franchises in HIV and HCV.

Governance factors are a moderately positive consideration in our credit rating analysis because of the company's record of good execution of its strategies, consistent financial performance, and deep management expertise.

Panel B presents an illustrative example of an ESG score adapted from an issuer credit rating report. Source: S&P Capital IQ RatingsXpress (Gilead Sciences Inc., February 9, 2023).

Environmental, Social, And Governance

ESG Credit Indicators

E-1	E-2	E-3	E-4	**E-5**	S-1	S-2	S-3	S-4	**S-5**	G-1	G-2	G-3	G-4	**G-5**

- Climate transition risks - Physical risks	- Health and safety - Social capital	- Governance structure - Risk management, culture, and oversight

ESG credit indicators provide additional disclosure and transparency at the entity level and reflect S&P Global Ratings' opinion of the influence that environmental, social, and governance factors have on our credit rating analysis. They are not a sustainability rating or an S&P Global Ratings ESG Evaluation. The extent of the influence of these factors is reflected on an alphanumerical 1-5 scale where 1 = positive, 2 = neutral, 3 = moderately negative, 4 = negative, and 5 = very negative. For more information, see our commentary "ESG Credit Indicator Definitions And Applications," published Oct. 13, 2021.

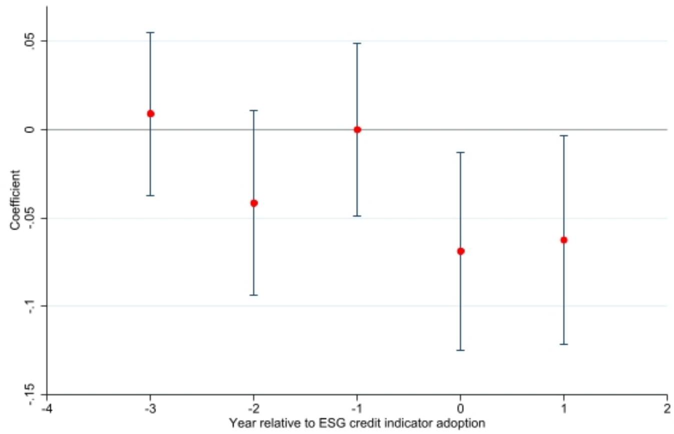
Environmental, social, and governance factors are very negative considerations. Climate change has increased the frequency of wildfires in northern California and environmental factors have become an integral part of our credit analysis of the company.

Social risks are also high, reflecting its communities' susceptibility to wildfires and the potential for higher customer bills due to continued significant investments in wildfire mitigation, system hardening, and technology.

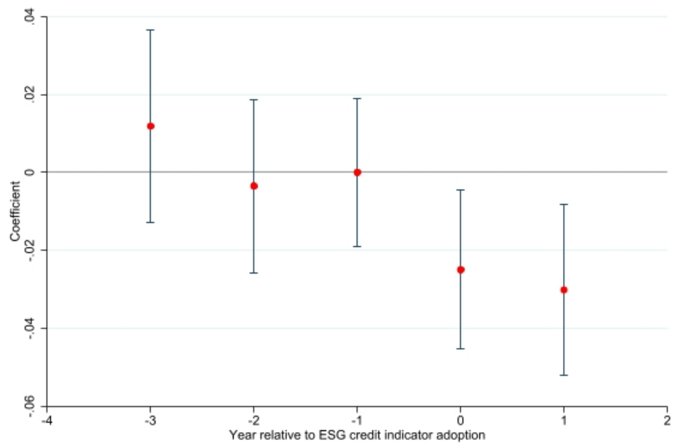
Governance factors are also a very negative consideration. The company is the only North American regulated utility to file for bankruptcy protection twice over the past two decades and has a history of confrontational relationships with regulatory authorities, which, in our view, are beyond isolated episodes and outside industry norms. This has hurt the company's reputation, representing a significant risk.

Panel C presents an illustrative example of an ESG score adapted from an issuer credit rating report. Source: S&P Capital IQ RatingsXpress (Pacific Gas & Electric Co., February 13, 2023).

Figure 2: Dynamic DiD estimates of bond market liquidity measures



(a) Effective bid–ask spread



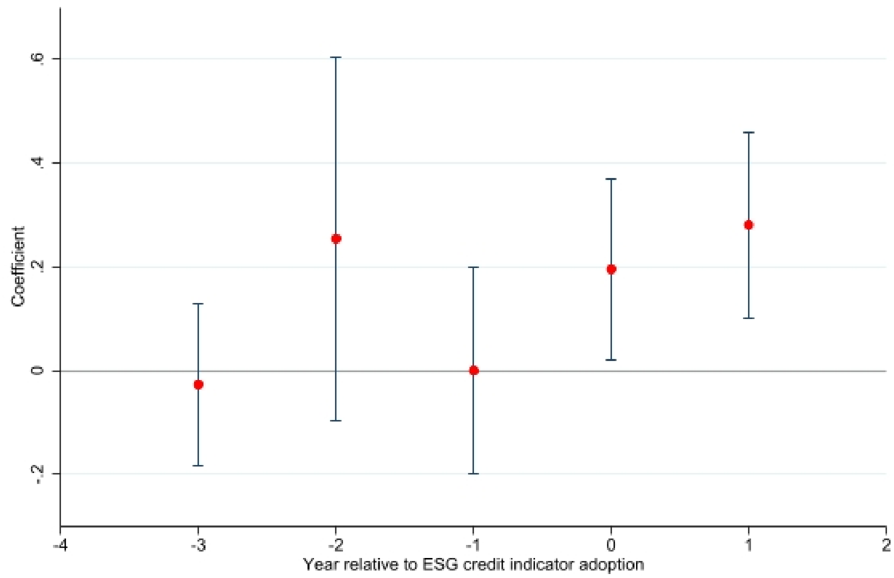
(b) Bid–ask spread volatility

Panels A and B presents the event-time treatment-effect coefficients from the following dynamic DiD regression estimated on the entropy-balanced sample:

$$Med\_BidAsk_{i,t+1}/Spread\_Vol_{i,t+1} = \beta_1 + \sum_{k=-3}^{+1} \beta_k \big(D_k \times ESG\_Covered_i\big) + \gamma\, Controls_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{i,t}$$

where event time is defined relative to the adoption of ESG credit indicators in September 2021 ($t = 0$). The analysis covers the period from September 2018 through August 2023. The base period corresponds to event time $k = -1$, which spans September 2020 through August 2021. Event time $k = 0$ covers the period from September 2021 through August 2022. D_k is an indicator equal to one if the observation falls in event-time period k relative to adoption and zero otherwise. Control variables include *Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, *ROA*, *SP_Rating*, *Coverage_Ratio*, *Coupon*, *LnMaturity*, and *Offering_Amount*. The figure plots the annual β_k coefficients along with 95% confidence intervals. Standard errors are clustered at the bond level. Variable definitions are provided in Appendix 2.

Figure 3: Dynamic DiD estimates of bond market reactions

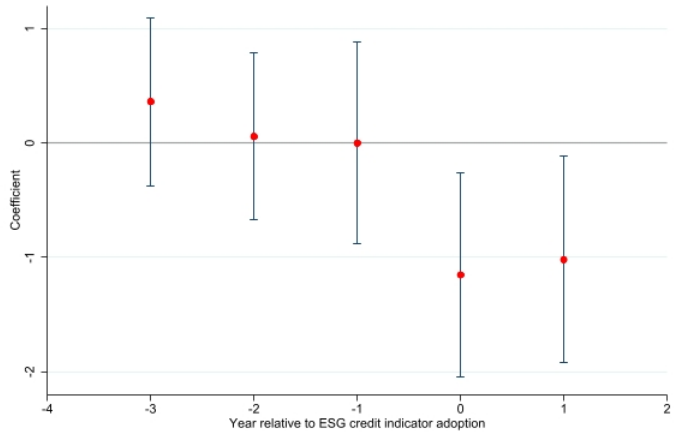


This figure presents the event-time treatment-effect coefficients from the following dynamic DiD regression estimated on the entropy-balanced sample:

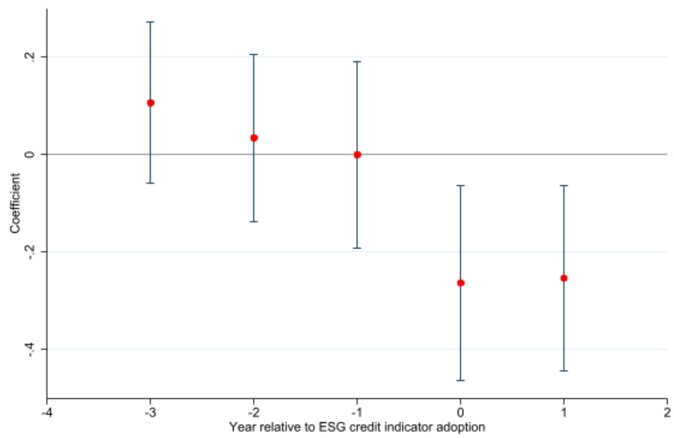
$$AbsCAR[-3,3]_{i,t} = \beta_1 + \sum_{k=-3}^{+1} \beta_k \big(D_k \times ESG\_Covered_i\big)$$
$$+\, \gamma\, Controls_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{i,t}$$

where event time is defined relative to the adoption of ESG credit indicators in September 2021 ($t = 0$). The analysis covers the period from September 2018 through August 2023. The base period corresponds to event time $k = -1$, which spans September 2020 through August 2021. Event time $k = 0$ covers the period from September 2021 through August 2022. D_k is an indicator equal to one if the observation falls in event-time period k relative to adoption and zero otherwise. Control variables include ΔSP_Rating, *ESGTone*, *ESG_Length*, *Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, *Report_Length*, *Report_Tone*, *ROA*, *SP_Rating*, and *Coverage_Ratio*. The figure plots the annual β_k coefficients along with 95% confidence intervals. Standard errors are clustered at the bond level. Variable definitions are provided in Appendix 2.

Figure 4: Dynamic DiD estimates of ESG narrative content measures



(a) Proportion of ESG narrative content



(b) Length of ESG narrative content

Panels A and B present the event-time treatment-effect coefficients from the following dynamic DiD regression estimated on the entropy-balanced sample:

$$ESG\_Prop_{i,t}/ESG\_Length_{i,t} = \beta_1 + \sum_{k=-3}^{+1} \beta_k \big(D_k \times ESG\_Covered_i\big) + \gamma\ Controls_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{i,t}$$

where event time is defined relative to the adoption of ESG credit indicators in September 2021 ($t = 0$). The analysis covers the period from September 2018 through August 2023. The base period corresponds to event time $k = -1$, which spans September 2020 through August 2021. Event time $k = 0$ covers the period from September 2021 through August 2022. D_k is an indicator equal to one if the observation falls in event-time period k relative to adoption and zero otherwise. Control variables include *Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, *Report_Length*, *Report_Tone*, and *ROA*. The figure plots the annual β_k coefficients along with 95% confidence intervals. Standard errors are clustered at the firm level. Variable definitions are provided in Appendix 2.

Table 1: Summary statistics and correlation matrix

	N	Mean	SD	Min	P25	Median	P75	Max
Panel A:Credit rating report variables								
ESGScore	922	-2.122	0.324	-3.000	-2.333	-2.000	-2.000	-1.667
EScore	922	-2.231	0.541	-4.000	-2.000	-2.000	-2.000	-2.000
SScore	922	-2.142	0.452	-4.000	-2.000	-2.000	-2.000	-2.000
GScore	922	-1.993	0.508	-3.000	-2.000	-2.000	-2.000	-1.000
ESGTone	5325	-0.303	33.867	-100.000	0.000	0.000	0.000	100.000
ETone	5325	-2.028	29.306	-100.000	0.000	0.000	0.000	100.000
STone	5325	-1.851	33.802	-100.000	0.000	0.000	0.000	100.000
GTone	5325	5.681	30.164	-100.000	0.000	0.000	0.000	100.000
ESG_Prop	5325	4.327	5.688	0.000	0.000	1.923	6.818	27.273
ESG_Length	5325	0.773	0.903	0.000	0.000	0.000	1.609	2.708
ESG_Spec	5325	1.441	2.579	0.000	0.000	0.000	2.041	11.538
ESG_FLS	5325	6.912	13.585	0.000	0.000	0.000	9.091	60.000
Panel B: Bond-level variables								
Avg_BidAsk (t+1)	32489	0.506	0.522	0.077	0.228	0.362	0.596	2.502
Med_BidAsk (t+1)	32489	0.393	0.469	0.056	0.170	0.262	0.433	2.356
Spread_Vol (t+1)	13933	0.057	0.099	0.000	0.010	0.021	0.049	0.590
GSpread_Vol (t+1)	13267	0.433	0.663	0.026	0.140	0.224	0.421	4.361
AbsCAR [-3, 3]	14569	0.654	0.902	0.004	0.132	0.360	0.773	5.662
CAR [-3, 3]	14569	0.001	1.003	-3.924	-0.360	-0.018	0.360	3.853
Coupon	33040	4.193	1.581	0.900	3.125	4.000	5.100	8.500
Coverage_Ratio	33040	11.373	11.404	-3.132	4.444	7.976	13.905	53.210
Maturity	33040	4.551	0.896	2.646	3.919	4.494	5.361	6.179
Offering_Amount	33040	0.961	0.874	0.069	0.500	0.750	1.200	4.250
Panel C: Report-level outcome variables								
SP_Rating	4906	12.305	3.031	6.000	10.000	13.000	14.000	20.000
SP_Rating (t+1)	4890	12.295	3.079	5.000	10.000	13.000	14.000	20.000
ROA (t+1)	5263	0.079	0.072	-0.096	0.031	0.065	0.112	0.338
EBITDA_Margin (t+1)	4957	0.248	0.176	-0.193	0.124	0.209	0.354	0.768
Earnings_Vol	4233	0.024	0.029	0.001	0.006	0.013	0.029	0.139
Panel D: Report-level control variables								
ESG_Covered	5325	0.600	0.490	0.000	0.000	1.000	1.000	1.000
Leverage	5325	0.329	0.209	0.001	0.178	0.314	0.440	0.995
Loss	5325	0.128	0.334	0.000	0.000	0.000	0.000	1.000
LSEG_ESGScore	4845	7.338	2.253	2.000	6.000	8.000	9.000	11.000
LSEG_EScore	4845	6.344	3.219	1.000	4.000	7.000	9.000	12.000
LSEG_GScore	4845	7.616	2.460	2.000	6.000	8.000	10.000	12.000
LSEG_SScore	4845	7.670	2.656	1.000	6.000	8.000	10.000	12.000
MktCap	5325	9.263	1.781	5.127	8.005	9.212	10.514	13.732
Mkt_to_Book	5325	4.052	9.673	-32.238	1.312	2.250	4.466	57.523
Report_Length	5325	4.215	0.486	2.890	4.007	4.304	4.533	5.176
Report_Tone	5325	16.837	14.500	-21.622	7.547	16.901	27.027	49.275
ROA	5325	0.080	0.073	-0.108	0.031	0.067	0.114	0.338
Tangibility	5017	0.224	0.239	0.000	0.037	0.126	0.349	0.858
ΔSP_Rating	4550	0.424	0.789	-1.000	0.000	0.000	1.000	2.000

Table 1: (continued)

Panel E: Correlation matrix			
	EScore	SScore	GScore
ETone	0.360		
STone		0.116	
GTone			0.028
	EScore	SScore	GScore
LSEG_EScore	0.036		
LSEG_SScore		0.050	
LSEG_GScore			-0.185

Notes: This table reports, for each variable, the mean, standard deviation (SD), minimum, 25th percentile (P25), median, 75th percentile (P75), and maximum. Panel A presents ESG variables from S&P credit rating reports. Panel B reports bond-level variables. Panel C reports the outcome variables measured at the report level. Panel D reports the control variables measured at the report level. Panel E presents Spearman and Pearson correlations between S&P ESG credit indicators and ESG tone, as well as Spearman and Pearson correlations between S&P ESG credit indicators and third-party LSEG ESG scores. Variable definitions are provided in Appendix 2.

Table 2: Determinants of S&P publishing ESG credit indicators

Panel A: Logit regression results	
	ESG_Covered
	(1)
Leverage	0.927**
	(0.462)
Loss	-0.571***
	(0.169)
MktCap	0.341***
	(0.062)
Mkt_to_Book	-0.010*
	(0.006)
ROA	0.014
	(1.093)
Industry FE	Y
Year FE	Y
Observations	5,325
Adjusted R2̂	0.179

Panel B.1: Before entropy balancing			
	ESG_Covered = 1 N = 3,193 (1)	ESG_Covered = 0 N = 2,132 (2)	(2) - (1) (3)
Leverage	0.345	0.304	-0.041***
Loss	0.105	0.161	0.056***
MktCap	9.625	8.720	-0.905***
Mkt_to_Book	4.602	3.228	-1.374***
ROA	0.090	0.065	-0.025***

Panel B.2: After entropy balancing			
	ESG_Covered = 1 N = 3,193 (1)	ESG_Covered = 0 N = 2,132 (2)	(2) - (1) (3)
Leverage	0.345	0.345	0.000
Loss	0.105	0.105	0.000
MktCap	9.625	9.625	0.000
Mkt_to_Book	4.602	4.602	0.000
ROA	0.090	0.090	0.000

Notes: Panel A presents the results of a logit regression on the determinants of S&P's publication of ESG credit indicators. The dependent variable equals one if S&P published ESG credit indicators in the firm's credit rating report at least once between Sept. 2021 and Aug. 2023, and zero otherwise. Standard errors are reported in parentheses and are clustered at the firm level. All specifications include industry and year fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Panel B.1 reports the means of the determinant variables for firms with and without ESG credit indicator coverage and the difference in means prior to entropy balancing. Panel B.2 reports the corresponding means and differences after entropy balancing.

Table 3: Adoption and withdrawal of ESG credit indicators and bond market information asymmetry

	Avg_BidAsk (t+1)		Med_BidAsk (t+1)	
	(1)	(2)	(3)	(4)
Adopt × ESG_Covered	-0.047***		-0.036**	
	(0.017)		(0.016)	
Adopt	0.241***		0.215***	
	(0.032)		(0.034)	
Abandon × ESG_Covered		0.025*		0.037***
		(0.013)		(0.014)
Abandon		-0.072***		-0.084***
		(0.013)		(0.014)
Coupon	0.089***	0.070***	0.080***	0.063***
	(0.005)	(0.006)	(0.005)	(0.005)
Coverage_Ratio	0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
ESGTone	0.000	0.000**	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
ESG_Length	0.011***	-0.007*	0.007*	-0.006
	(0.004)	(0.004)	(0.004)	(0.005)
Leverage	-0.284**	0.066	-0.181*	0.049
	(0.116)	(0.129)	(0.099)	(0.144)
Loss	0.030	-0.009	0.014	-0.025
	(0.023)	(0.038)	(0.016)	(0.028)
Maturity	0.168***	0.154***	0.133***	0.117***
	(0.006)	(0.008)	(0.005)	(0.007)
MktCap	0.001	0.061***	-0.003	0.066***
	(0.019)	(0.021)	(0.014)	(0.020)
Mkt_to_Book	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Offering_Amount	-0.129***	-0.131***	-0.111***	-0.114***
	(0.019)	(0.015)	(0.015)	(0.014)
Report_Length	-0.001	0.008*	0.000	0.004
	(0.009)	(0.004)	(0.009)	(0.004)
Report_Tone	-0.001*	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.280	-0.200	-0.295	-0.200
	(0.195)	(0.209)	(0.198)	(0.219)
SP_Rating	0.009	-0.021	0.012*	-0.014
	(0.008)	(0.016)	(0.007)	(0.015)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	25,006	16,831	25,006	16,831
Adjusted R^2	0.373	0.352	0.329	0.305

Notes: This table investigates how the adoption and subsequent withdrawal of ESG credit indicators relate to transaction-based secondary-bond-market information asymmetry, using indicators for adoption (*Adopt*) and abandonment (*Abandon*) interacted with the ESG coverage indicator. The analysis uses a matched sample constructed via entropy balancing based on *Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*. Standard errors are reported in parentheses and are clustered at the bond level. All specifications include year fixed effects. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Adoption and withdrawal of ESG credit indicators and bond market liquidity

	Spread_Vol (t+1)		GSpread_Vol (t+1)	
	(1)	(2)	(3)	(4)
Adopt × ESG_Covered	-0.027***		-0.090**	
	(0.010)		(0.036)	
Adopt	0.006		0.103**	
	(0.008)		(0.045)	
Abandon × ESG_Covered		-0.004		0.006
		(0.006)		(0.026)
Abandon		0.007		-0.063***
		(0.005)		(0.021)
Coupon	0.001	-0.000	-0.037***	-0.054***
	(0.001)	(0.001)	(0.008)	(0.011)
Coverage_Ratio	-0.000	-0.000	-0.002	0.005*
	(0.000)	(0.000)	(0.002)	(0.003)
ESGTone	-0.000***	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ESG_Length	-0.004***	0.003*	-0.026***	-0.008
	(0.001)	(0.002)	(0.008)	(0.008)
Leverage	0.031	-0.033	-0.150	-0.372**
	(0.025)	(0.026)	(0.151)	(0.171)
Loss	-0.003	0.001	0.087***	-0.023
	(0.005)	(0.005)	(0.029)	(0.028)
Maturity	0.011***	-0.001	-0.085***	-0.115***
	(0.002)	(0.002)	(0.010)	(0.013)
MktCap	-0.010	-0.014	-0.137***	-0.120***
	(0.007)	(0.010)	(0.035)	(0.037)
Mkt_to_Book	0.000	0.000	-0.000	0.002**
	(0.000)	(0.000)	(0.001)	(0.001)
Offering_Amount	0.001	-0.000	-0.049***	-0.051***
	(0.003)	(0.005)	(0.014)	(0.019)
Report_Length	-0.005*	0.002*	0.095***	0.006
	(0.003)	(0.001)	(0.019)	(0.007)
Report_Tone	0.000***	-0.000**	-0.001*	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
ROA	0.162***	0.014	0.229	-0.978***
	(0.063)	(0.064)	(0.347)	(0.291)
SP_Rating	-0.001	0.016	-0.032	0.053
	(0.003)	(0.011)	(0.030)	(0.043)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	10,254	8,220	9,729	7,907
Adjusted R^2	0.380	0.342	0.499	0.560

Notes: This table investigates how the adoption and subsequent withdrawal of ESG credit indicators relate to quote-based secondary-bond-market information frictions, using indicators for adoption (*Adopt*) and abandonment (*Abandon*) interacted with the ESG coverage indicator. The analysis uses a matched sample constructed via entropy balancing based on *Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*. Standard errors are reported in parentheses and are clustered at the bond level. All specifications include firm and year fixed effects. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Adoption and withdrawal of ESG credit indicators and bond market reactions

	AbsCAR $[-3, 3]$	
	(1)	(2)
Adopt × ESG_Covered	0.159**	
	(0.068)	
Adopt	-0.198***	
	(0.057)	
Abandon × ESG_Covered		-0.081
		(0.053)
Abandon		0.141***
		(0.048)
ESG_Covered	-0.133***	-0.002
	(0.042)	(0.052)
ΔSP_Rating	0.135***	-0.024
	(0.025)	(0.022)
Coupon	-0.020**	-0.044***
	(0.010)	(0.010)
Coverage_Ratio	0.003	0.008***
	(0.002)	(0.002)
ESGTone	0.002***	0.001***
	(0.000)	(0.000)
ESG_Length	0.003	0.013
	(0.016)	(0.022)
Leverage	0.590***	0.587***
	(0.150)	(0.125)
Loss	0.001	0.170**
	(0.049)	(0.067)
Maturity	0.131***	0.094***
	(0.015)	(0.013)
MktCap	-0.072***	-0.106***
	(0.013)	(0.016)
Mkt_to_Book	-0.000	-0.000
	(0.001)	(0.002)
Offering_Amount	0.059**	0.058**
	(0.028)	(0.029)
Report_Length	-0.127***	0.002
	(0.029)	(0.022)
Report_Tone	-0.001	-0.001
	(0.001)	(0.001)
ROA	-1.379***	-1.099***
	(0.379)	(0.345)
SP_Rating	-0.027***	-0.016
	(0.009)	(0.010)
Year FE	Y	Y
Observations	9,843	7,886
Adjusted R^2	0.140	0.113

Notes: This table investigates how the adoption and subsequent withdrawal of ESG credit indicators relate to quote-based secondary-bond-market reactions, using indicators for adoption (*Adopt*) and abandonment (*Abandon*) interacted with the ESG coverage indicator. The analysis uses a matched sample constructed via entropy balancing based on *Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*. Standard errors are reported in parentheses and are clustered at the bond level. All specifications include year fixed effects. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Relationship between ESG credit indicators and bond market reactions

	CAR [-3, 3]					
	(1)	(2)	(3)	(4)	(5)	(6)
ESGScore × ΔSP_Rating				-0.005	-0.021	-0.017
				(0.063)	(0.064)	(0.064)
ESGScore	0.369***	0.242**	0.261***	0.369***	0.243***	0.262***
	(0.073)	(0.094)	(0.095)	(0.072)	(0.093)	(0.094)
ESGTone		0.002**	0.002***		0.002**	0.002***
		(0.001)	(0.001)		(0.001)	(0.001)
LSEG_ESGScore			0.040*			0.040*
			(0.021)			(0.021)
ΔSP_Rating	0.077**	0.094***	0.107***	0.066	0.048	0.070
	(0.032)	(0.034)	(0.035)	(0.146)	(0.148)	(0.150)
Coupon	-0.004	-0.002	0.005	-0.004	-0.002	0.005
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.014)
Coverage_Ratio	-0.002	-0.000	0.008	-0.002	0.000	0.008
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)
ESG_Length	0.022	0.010	0.002	0.022	0.010	0.002
	(0.038)	(0.039)	(0.040)	(0.038)	(0.039)	(0.040)
Leverage	0.301	0.386	0.489**	0.303	0.393	0.495**
	(0.230)	(0.235)	(0.246)	(0.234)	(0.239)	(0.250)
Loss	-0.162	-0.201	-0.235*	-0.162	-0.204	-0.237*
	(0.129)	(0.130)	(0.136)	(0.130)	(0.131)	(0.137)
Maturity	-0.039*	-0.042*	-0.045*	-0.039*	-0.043*	-0.045**
	(0.022)	(0.022)	(0.023)	(0.022)	(0.023)	(0.023)
MktCap	-0.005	-0.023	-0.029	-0.005	-0.023	-0.029
	(0.029)	(0.030)	(0.032)	(0.029)	(0.030)	(0.032)
Mkt_to_Book	0.002	0.002	0.001	0.002	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Offering_Amount	-0.157***	-0.137***	-0.139***	-0.157***	-0.136***	-0.138***
	(0.048)	(0.049)	(0.048)	(0.048)	(0.050)	(0.048)
Report_Length	-0.071	-0.040	-0.053	-0.071	-0.039	-0.052
	(0.051)	(0.053)	(0.053)	(0.052)	(0.054)	(0.054)
Report_Tone	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	-2.218***	-2.433***	-3.076***	-2.221***	-2.447***	-3.082***
	(0.542)	(0.550)	(0.695)	(0.546)	(0.556)	(0.696)
SP_Rating	0.016	0.026	0.013	0.015	0.026	0.013
	(0.016)	(0.017)	(0.019)	(0.016)	(0.017)	(0.019)
Year FE	Y	Y	Y	Y	Y	Y
Observations	2,464	2,464	2,318	2,464	2,464	2,318
Adjusted R^2	0.032	0.035	0.040	0.032	0.035	0.040

Notes: This table examines bond-market reactions to the aggregate S&P ESG credit indicator, including tests of whether the relation between ESG credit indicators and bond-market returns depends on contemporaneous credit rating changes. The sample period is restricted to 2021–2023 due to the availability of ESG credit indicators. Standard errors are reported in parentheses and are clustered at the bond level. All specifications include year fixed effects. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: ESG credit indicators and credit ratings

	SP_Rating			SP_Rating (t+1)		
	(1)	(2)	(3)	(4)	(5)	(6)
ESGScore	1.581***	1.603***	1.642***	1.495***	1.516***	1.569***
	(0.229)	(0.246)	(0.254)	(0.242)	(0.259)	(0.258)
ESGTone		-0.000	-0.001		-0.000	-0.001
		(0.001)	(0.001)		(0.001)	(0.001)
LSEG_ESGScore			0.119***			0.113***
			(0.032)			(0.032)
ESG_Length	0.212***	0.213***	0.200***	0.177**	0.179**	0.174**
	(0.074)	(0.073)	(0.073)	(0.074)	(0.074)	(0.073)
Leverage	-3.065***	-3.066***	-3.251***	-3.280***	-3.281***	-3.427***
	(0.341)	(0.341)	(0.356)	(0.374)	(0.374)	(0.380)
Loss	-0.517***	-0.514***	-0.512**	-0.561***	-0.558***	-0.401**
	(0.193)	(0.193)	(0.208)	(0.205)	(0.205)	(0.204)
MktCap	1.090***	1.090***	1.007***	1.103***	1.104***	1.037***
	(0.048)	(0.049)	(0.055)	(0.050)	(0.051)	(0.056)
Mkt_to_Book	0.008	0.008	0.009	0.008	0.008	0.009
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Report_Length	0.045	0.044	-0.044	0.090	0.089	-0.066
	(0.109)	(0.109)	(0.100)	(0.116)	(0.116)	(0.100)
Report_Tone	0.011**	0.011**	0.012***	0.011***	0.011***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ROA	4.968***	4.976***	5.432***	5.167***	5.176***	5.526***
	(1.104)	(1.104)	(1.154)	(1.117)	(1.117)	(1.139)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	892	892	831	888	888	829
Adjusted R^2	0.777	0.777	0.776	0.769	0.769	0.775

Notes: This table investigates whether aggregate S&P ESG credit indicators are incorporated into contemporaneous and subsequent credit ratings. The sample period is restricted to 2021–2023 due to the availability of ESG credit indicators. Standard errors are reported in parentheses and are clustered at the firm level. All specifications include industry and year fixed effects. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Relationship between ESG credit indicators and future firm financial performance

	ROA (t+1)			EBITDA_Margin (t+1)			Earnings_Vol		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ESGScore	-0.003	-0.001	-0.001	0.026*	0.030**	0.025	-0.007*	-0.008**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.014)	(0.015)	(0.016)	(0.003)	(0.004)	(0.004)
ESGTone		-0.000	-0.000*		-0.000	-0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
LSEG_ESGScore			0.001			-0.005*			-0.000
			(0.001)			(0.003)			(0.001)
ESG_Length	-0.001	-0.001	-0.002	-0.005	-0.005	-0.006	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Leverage	0.049***	0.048***	0.048***	0.111***	0.110***	0.103***	-0.012	-0.012	-0.011
	(0.009)	(0.009)	(0.009)	(0.030)	(0.030)	(0.032)	(0.007)	(0.007)	(0.008)
Loss	-0.002	-0.001	-0.000	-0.023	-0.023	-0.031*	0.011***	0.011***	0.011***
	(0.005)	(0.005)	(0.005)	(0.015)	(0.015)	(0.016)	(0.004)	(0.004)	(0.004)
MktCap	0.004***	0.004***	0.004***	0.014***	0.014***	0.020***	-0.002***	-0.002***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Mkt_to_Book	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Report_Length	-0.004	-0.004	-0.004*	0.001	0.001	0.000	-0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)	(0.002)	(0.002)	(0.002)
Report_Tone	0.000***	0.000***	0.000***	0.000	0.000*	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.791***	0.792***	0.808***	0.551***	0.553***	0.544***	0.128***	0.128***	0.131***
	(0.029)	(0.029)	(0.030)	(0.072)	(0.073)	(0.076)	(0.022)	(0.022)	(0.022)
Tangibility	-0.007	-0.008	-0.005	0.089***	0.089***	0.107***	0.009	0.009	0.008
	(0.007)	(0.007)	(0.007)	(0.032)	(0.032)	(0.032)	(0.005)	(0.005)	(0.005)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	859	859	813	854	854	808	751	751	726
Adjusted R^2	0.785	0.785	0.789	0.523	0.523	0.541	0.291	0.291	0.299

Notes: This table investigates the relationship between firms' future financial performance and aggregate S&P ESG credit indicators. The sample period is restricted to 2021–2023 due to the availability of ESG credit indicators. Standard errors are reported in parentheses and are clustered at the firm level. All specifications include industry and year fixed effects. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Adoption and withdrawal of ESG credit indicators and ESG narrative content

	ESG_Prop		ESG_Length		ESG_Spec		ESG_FLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Adopt × ESG_Covered	-1.037**		-0.168**		-0.275		-2.481**	
	(0.444)		(0.072)		(0.213)		(1.246)	
Adopt	0.090		0.074		0.163		3.442	
	(0.505)		(0.093)		(0.257)		(2.104)	
Abandon × ESG_Covered		0.604		0.101		0.007		1.932
		(0.665)		(0.070)		(0.223)		(1.488)
Abandon		-1.994**		-0.255***		-0.323		-3.389**
		(0.813)		(0.086)		(0.221)		(1.534)
Leverage	4.610***	7.350**	0.529**	0.410	-0.743	1.806	2.279	-5.734
	(1.363)	(3.178)	(0.237)	(0.357)	(0.723)	(1.410)	(3.981)	(6.471)
Loss	0.130	-0.363	0.048	-0.031	-0.095	-0.132	1.125	0.765
	(0.329)	(0.545)	(0.059)	(0.065)	(0.198)	(0.287)	(1.009)	(1.048)
MktCap	0.534*	1.094	0.029	0.009	0.068	0.421*	-0.612	0.879
	(0.306)	(0.703)	(0.057)	(0.074)	(0.155)	(0.226)	(0.853)	(1.378)
Mkt_to_Book	-0.007	0.006	-0.002	0.002	0.001	0.008	0.073	0.056
	(0.011)	(0.028)	(0.002)	(0.003)	(0.003)	(0.006)	(0.047)	(0.055)
Report_Length	-2.138***	-3.614***	0.523***	0.352***	1.002***	0.738***	3.871***	3.896***
	(0.441)	(0.448)	(0.051)	(0.042)	(0.150)	(0.127)	(0.685)	(0.852)
Report_Tone	-0.016	-0.034	-0.002	-0.003	-0.005	-0.001	-0.005	-0.074*
	(0.011)	(0.023)	(0.002)	(0.003)	(0.004)	(0.007)	(0.021)	(0.038)
ROA	0.494	2.482	0.147	0.303	0.315	0.756	17.054**	9.682
	(2.542)	(4.347)	(0.371)	(0.412)	(1.608)	(3.274)	(6.738)	(11.598)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,954	2,504	3,954	2,504	3,954	2,504	3,954	2,504
Adjusted R^2	0.444	0.390	0.511	0.580	0.424	0.559	0.345	0.538

Notes: This table investigates how the adoption and subsequent withdrawal of ESG credit indicators relate to the volume and characteristics of ESG narrative content, using indicators for adoption (*Adopt*) and abandonment (*Abandon*) interacted with the ESG coverage indicator. The analysis uses a matched sample constructed via entropy balancing based on *Leverage*, *Loss*, *MktCap*, *Mkt_to_Book*, and *ROA*. Standard errors are reported in parentheses and are clustered at the firm level. All specifications include firm and year fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Relationship between ESG credit indicators and ESG narrative content

	ESG_Prop	ESG_Length	ESG_Spec	ESG_FLS
	(1)	(2)	(3)	(4)
ESGScore	-2.300***	-0.505***	-0.518	-2.457
	(0.779)	(0.124)	(0.471)	(2.162)
Leverage	1.762	0.216	-0.375	5.280
	(1.076)	(0.163)	(0.600)	(3.411)
Loss	0.184	0.038	-0.041	-4.697**
	(0.575)	(0.092)	(0.341)	(1.861)
MktCap	0.919***	0.141***	0.368***	0.851**
	(0.142)	(0.019)	(0.075)	(0.360)
Mkt_to_Book	0.006	0.001	0.002	0.035
	(0.024)	(0.003)	(0.008)	(0.058)
Report_Length	-3.703***	0.409***	0.738***	1.789*
	(0.513)	(0.051)	(0.211)	(1.011)
Report_Tone	-0.036**	-0.005**	-0.010	0.031
	(0.018)	(0.002)	(0.008)	(0.042)
ROA	-2.932	-0.315	-1.271	-21.578**
	(2.782)	(0.397)	(1.642)	(9.553)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	922	922	922	922
Adjusted R^2	0.231	0.254	0.165	0.064

Notes: This table investigates the association between the volume and characteristics of ESG narrative content and the level of aggregate S&P ESG credit indicators in credit rating reports. The sample period is restricted to 2021–2023 due to the availability of ESG credit indicators. Standard errors are reported in parentheses and are clustered at the firm level. All specifications include industry and year fixed effects. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.