ESG information and the quality of credit ratings: Evidence from S&P's acquisition of RobecoSAM

Riddha Basu
George Washington University
rbasu@gwu.edu

Aaron Yoon
Kellogg School of Management
Northwestern University
aaron.yoon@kellogg.northwestern.edu

Jian Zhou
University of Hawaii
jianzhou@hawaii.edu

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Abstract

We investigate whether and how the information quality of credit rating changes when a large credit rating agency acquires a prominent ESG information provider and provides ESG ratings to credit rating clients. We take the case of S&P's acquisition RobecoSAM and find that the credit ratings of firms covered by RobecoSAM before the merger become more responsive to credit risk. We find that this effect is driven by the firms that S&P highlights ESG as an important factor in credit risk, experience an increase in downside ESG risk, and likely need more due diligence in generating more relevant credit ratings. Lastly, we find that the changes in credit ratings contain more stock price relevant information after S&P acquired RobecoSAM. Overall, our results suggest that ESG information made S&P's credit ratings more relevant.

Keywords: ESG information, credit ratings, information quality

JEL Codes: G12, G14

1. Introduction

Because of the exponential growth in ESG investing and corporate issuers' claims on ESG as an important business strategy, many traditional financial information providers and analytics companies have entered into the ESG ratings and consulting business. For example, major credit raters such as S&P and Moody's recently acquired ESG raters and started issuing ESG ratings, and a small number of financial analysts now explicitly embed ESG factors in their analyst reports (Eaglesham 2022). The typical argument for credit rating agencies (CRAs) entering the ESG ratings space is that ESG risk is an important facet of the business risks that firms face, which fall under the broad umbrella of their expertise, and that they can leverage the existing financial and informational resources to produce better-quality ESG ratings (S&P 2019). To this end, recent papers assess the properties of ESG ratings when there are pre-existing commercial ties in providing user-paid credit ratings (Li, Lou, and Zhang 2022). However, we know little about whether and how ESG is related to, and impacts, the traditional risk (e.g., credit risk) that financial services firms have expertise and interest in.

Against this backdrop, we study whether and how the information quality of credit rating changes when a large credit rating agency provides ESG ratings to a credit rating client. Specifically, we take the case of S&P and its acquisition of RobecoSAM that occurred on November 21, 2019 and examine whether their credit ratings contain more information after the acquisition. We focus on credit raters rather than other prominent information intermediaries like equity analysts because major credit raters (i.e., S&P and Moody's) acquired ESG raters and are now issuing ESG ratings, whereas the trend on ESG rater acquisition or ESG-related information production is not as salient for the case of brokerage firms employing equity analysts (Park, Yoon, and Zach 2023).

We expect the information quality of S&P's credit ratings to improve after S&P's acquisition of RobecoSAM. One important reason is because information processing cost would likely decrease (Blankespoor, deHaan, and Marinovic 2020). The acquisition of RobecoSAM should have increased credit analysts' awareness towards ESG information since it was a significant event at S&P. After the RobecoSAM merger, S&P claimed that *"ESG factors play a prominent role in creditworthiness, and influence credit quality"* and introduced an ESG credit indicator that complements the assessment of existing credit rating analysis. Further, S&P made a substantial number of ESG-driven credit rating actions. For example, S&P made 392 ESG-driven credit rating actions in 2022, among which 147 are positive rating actions and 242 are negative rating actions.[1] In addition, having an ESG ratings arm could enable the credit rating side to avoid repeating the work that has already been performed by the ESG ratings side and help recognize the economy of scale on ESG information acquisition. This is more likely if ESG risk not only overlaps with but also provides synergetic insights to traditional credit risk that firms face. ESG information considered alongside of traditional credit risk information could be beneficial, if it diminishes the cognitive burden for credit analysts required for synthesizing information and enable them to produce more relevant ratings (Bloomfield, Hodge, Hopkins, and Rennekamp 2015).

Further, the credit ratings side can also benefit from RobecoSAM's specialty of acquiring and integrating ESG information that is relevant in assessing credit risks. This is likely since RobecoSAM has 20 years of experience and expertise, and is a market leader in processing, analyzing, and interpreting ESG information. In essence, S&P may benefit from RobecoSAM's expertise in ESG rating and update its credit rating evaluations based on the newly acquired ESG

[1] https://www.spglobal.com/_assets/documents/esg-in-cr-newsletter_jan2024_no-link.pdf

rating and related information. Such an information channel also suggests that the merger could have less impact for firms that already have a strong information environment and require less due diligence for credit rating analysts. In sum, disclosure processing cost would likely have decreased for credit analysts after the merger.

On the other hand, given credit analysts are sophisticated users and processors of credit related firm information, such information awareness may not have any impact on the quality of credit ratings they produce. This is likely if ESG is purely operational and/or subsumed by the exiting works of credit raters (Edmans 2024). If so, ESG information may not add substantive value and may not improve the credit ratings quality. Further, given the need for marketing and attracting clients, it is not implausible for S&P to just reclassify what they viewed as credit risk to ESG risk (i.e., label what they have already been doing as "ESG"). Further, there is much confusion about what constitutes an ESG activity and no agreed-upon outcomes of ESG risks (Berg et al. 2022; Serafeim and Yoon 2022). If so, it may be difficult to map out the distinction between ESG and credit risk and to identify areas that can create synergies. In essence, processing and integrating ESG information may be too costly.

We also note a few reasons to expect the information quality of S&P's credit ratings to decrease after the acquisition of RobecoSAM. For example, conflicts of interest could arise when a CRA provides both credit and ESG ratings if the CRA can obtain a direct advantage, such as a future ESG consulting business. In such a case, S&P can offer biased credit ratings to credit clients to cater to their needs, which can potentially bias the ratings and hurt investors who use the credit ratings. This is a possible scenario given that S&P has disclosure guidance and consulting services available to corporate issuers to improve their ESG practices. Overall, this possible bias associated with the user-pay model of credit ratings can aggravate existing CRA's incentives to compromise credit rating quality and please their customers (Li et al. 2022). Hence, the merger would have less impact on information quality where the catering incentives are stronger.

We begin our analyses by investigating whether S&P credit ratings' information quality changes after S&P acquires RobecoSAM. To get at this, we first examine the responsiveness of credit ratings to credit risk before and after the RobecoSAM acquisition. We measure the responsiveness of credit ratings to credit risk by examining the relationship between credit ratings and the expected default frequency (EDF) following the prior literature (Xia 2014; Kedia et al. 2017) that used this test to identify the information effects of credit ratings. Our aim is to examine whether the group of firms that were already rated by RobecoSAM during the pre-merger period (henceforth, the "treated" firms) experience a change in their credit rating quality after the acquisition.

We find that the credit ratings of the treated group become more responsive to the expected default frequency after S&P acquires RobecoSAM vis-à-vis the group of firms that were not rated by RobecoSAM during the pre-merger period (henceforth, the "control" firms). Specifically, a standard deviation increase in EDF for the treated firms is associated with a 0.4 notch downgrade in S&P credit ratings after the merger. This magnitude implies that the merger has economically significant impact on the information quality of credit ratings issued by S&P. Overall, the results are consistent with the notion that ESG information improved the quality of credit ratings.

Next, we perform a few cross-sectional tests to support the role of ESG information in making credit ratings more informative. Specifically, we identify firm-years that (i) S&P identifies ESG factors as relevant to credit ratings (see Appendix B for details) and (ii) have heightened ESG risk. If our main results discussed above are indeed driven by more ESG information post the RobecoSAM acquisition, we should expect an improvement in S&P credit rating quality for firms where ESG is a relevant risk for credit ratings purposes. Indeed, we find that the rating quality improvement is driven by the group of firms that S&P identifies as considering ESG a relevant input in their credit rating process, and that this effect is driven by negative as opposed to positive ESG factors. Further, we find that credit rating quality improvement is driven by the group of firms that have heightened ESG risk. Both results suggest that credit ratings being more focused on the downside risk of a firm and that negative ESG risk related information is a relevant factor that improves credit ratings' quality.

Finally, we examine whether credit ratings contain more information content after S&P acquires RobecoSAM by using an additional proxy (i.e., based on the market reaction to credit ratings changes following Becker and Milbourn (2011) and Cheng and Neamtiu (2009). We find that the treated group experiences a negative and significant market-reaction (i.e., three-day cumulative abnormal returns) after credit rating downgrades in the post-merger period. We also find that the treated group experiences an increase in positive reaction after credit rating upgrades in the post-merger period. Overall, the results suggest that the availability of ESG ratings and the associated information transfer make S&P credit ratings more responsive to credit risk and also substantially increase the information content of S&P's rating changes in the post-merger period.

Our study has at least three contributions to the literature. First, we contribute to the literature that examines the information content of credit ratings. Prior studies on the information content of credit ratings did not provided much evidence on whether and how the provision of ESG ratings affects the information content of credit ratings (e.g., Jorion, Liu, and Shi 2005; Xia 2014; Livingston and Zhou 2016). Using a shock where a prominent CRA starts to provide both credit ratings and ESG ratings, we present novel evidence on the impact of ESG information on credit ratings where confounding factors influencing the information quality of credit ratings are less of a concern given the difference-in-difference research design afforded by the shock. To the best of our knowledge, our paper is the first study to document that credit rating has better information content when the CRA also provides ESG credit ratings.

Second, we contribute to the literature that examines the intersection of ESG and credit ratings, where both information transfer and conflict of interest can play a role in the interaction between the credit rating division and the ESG rating division of the CRAs. Literature finds that firms with better ESG performance exhibit better credit ratings (e.g., Attig, El Ghoul, Guedhami, and Suh 2013). Li et al. (2022) finds credit raters issue biased ESG ratings to their credit rating clients, pointing out that the independence and impartiality of the ESG rating process could be compromised by the credit rating business relationships.[2] More closely related to our work, Yang (2020) finds no evidence that the information quality of credit ratings improved after S&P and Moody's claim to incorporate ESG in 2015. We note that our paper has an opposite conclusion to Yang (2020), because we examine the impact of RobecoSAM's acquisition (an actual ESG rater) on the information quality of credit ratings. Overall, we extend this stream of literature by showing that ESG information adds value to the traditional risk assessment of credit raters.

Third, we extend the recent literature that examines ESG risk. Recently, it has been suggested that different ESG raters disagree on how to define, measure, and weigh ESG issues (Chatterji et al. 2016; Berg et al. 2022). The important takeaway in this debate is that we are still in the preliminary stage of understanding and defining ESG risk (Serafeim and Yoon 2022) and how it relates to the traditional risks that we already know in the literature (Park, Yoon, and Zach

[2] The information channel documented in our paper is significantly different from the conflict of interest documented in Li, Lou, and Zhang (2022). We argue that this is due to the difference in focus between these two papers and these two channels can co-exist. We focus on credit ratings, which are subject to regulatory scrutiny such as the supervision from the Office of Credit Ratings. The ESG ratings are relatively new and unregulated, which leaves ESG raters a much larger amount of discretion in granting ESG ratings. There is large divergence in ESG ratings since the prominent ESG rating agencies use different measurement and scope (Berg et al. 2022). The differences in measurement and scope allow ESG raters further discretion in granting ESG ratings.

2022). We add to this stream of nascent literature by showing that ESG information can improve the usefulness and information quality of credit ratings. This has important implications for both information intermediaries as well as asset managers because incorporating forward-looking ESG signals may improve the quality of credit ratings, which suggests that some part of ESG risk adds to existing credit risk. Our paper is timely because CRAs are beginning to devote more attention to ESG issues in response to their client demands.

2. Institutional setting and related research

2.1 Institutional setting

On November 21, 2019, S&P Global announced that it will acquire the ESG ratings business from RobecoSAM, which includes the widely followed Corporate Sustainability Assessment (CSA) framework that evaluates companies' sustainability practices. RobecoSAM's ESG rating business has two units: one that issues ESG Ratings to 4,700 companies and another that provides ESG consulting services to companies interested in understanding and improving their ESG practices. Since it has 20 years of experience and expertise in evaluating the role of ESG in a company's long-term value, the RobecoSAM ESG rating business has been considered one of the market leaders in the ESG rating and consulting industry with one of the most advanced ESG rating methodologies. According to S&P, *"Through this acquisition, S&P Global will be able to offer its clients even more transparent, robust and comprehensive ESG solutions."* [3] The acquisition of the RobecoSAM ESG rating business will help enhance S&P Global's position and reputation as a premier ESG insights and product solution provider for its clients.

We note that other major credit raters acquired ESG rating agencies in the same year. For

[3] https://www.prnewswire.com/news-releases/sp-global-to-acquire-the-esg-ratings-business-from-robecosam-300962951.html

example, Moody's acquired the ESG rating agency Vigeo Eiris on April 15, 2019. Moody's claims that *"ESG factors are taken into consideration for all credit ratings"* and it *"seeks to incorporate all issues that can materially impact credit quality, including ESG and climate risk; and aims to take the most forward-looking perspective that visibility into these risks and mitigants permits."* The common argument from the credit raters when acquiring ESG raters is that having an ESG ratings arm would enable the credit rating side to avoid repeating the work which has already been performed by the ESG rating side and help recognize the economy of scale on ESG information acquisition and processing.

We choose S&P Global's acquisition of RobecoSAM in this paper to investigate the impact of providing ESG ratings on the information quality of credit ratings because S&P holds the largest market share in the credit rating market. Hung, Kraft, Wang, and Yu (2022) define the market share of a CRA in a year (or a country) as the proportion of dollar value of new bonds rated by the CRA out of the total dollar value of all new bond issuances in a year (or a country) and find that S&P holds 93% of market share in the US between 1994 and 2019.[4]

2.2 Related literature

2.2.1 Drivers of credit ratings

For the drivers (determinants) of credit ratings, prior literature has considered both firms' and CRAs' incentives. Firms have incentives to maintain or seek better credit ratings since credit ratings have significant economic ramifications for firms. CRAs have conflicting incentives in generating credit ratings: the incentive to maintain a reputation in the capital market and the incentive to cater to clients since most CRAs such as S&P and Moody's rely on issuers to pay for

[4] We acknowledge that the market share of Moody's is only slightly less than S&P. According to Hung, Kraft, Wang, and Yu (2022), *"S&P and Moody's market shares are highly correlated over time and across countries."*

credit ratings.

Because credit ratings have significant economic implications for firms, managers often use discretion such as earnings management to influence credit ratings. Jung et al. (2013) find that managers smooth long-term earnings to reduce CRAs' credit risk perception. Firms with increased earnings smoothness are more likely to have rating upgrades in a subsequent period. Relatedly Alissa et al. (2013) provide evidence that firms manage earnings when they deviate from their expected ratings. They manage earnings down (up) when they are above (below) the expected credit ratings. Demirtas and Cornaggia (2013) find that firms have high and positive accruals around initial credit ratings, motivated by receiving favorable initial credit ratings. Liu et al. (2018) find that firms increase earnings management when they are on negative credit watch.

Credit ratings are also affected by CRAs' own conflict of interest. Conflict of interest has been documented widely in valuation analysis and stock recommendations of equity analysts and auditors' provision of non-audit services (Corwin, Laroque, and Stegemoller 2017; Shi, Teoh, and Zhou 2021). On the one hand, CRAs' reputation incentives lead to rating quality improvement and stringent ratings following events that threaten CRAs' reputation (Bolton et al. 2012). After Enron's accounting scandals, which has damaged the reputation of CRAs,[5] CRAs took action to improve their reputation and rating quality, such as accuracy, timeliness, and stability (Cheng and Neamtiu 2009). Similarly, deHaan (2017) documents credit quality improvement after the financial crisis. On the other hand, the issuer-pay model leads CRAs to issue favorable ratings, such as issuing favorable ratings to boost CRAs' business (Griffin and Tang 2011; Jiang et al. 2012; Kashyap and Kovrijnykh 2016). Consistent with the issuer-pay model weakening CRAs' ability to provide stringent ratings, Hung et al. (2022) find that lower market power of global CRAs

[5] CRAs such as Moody's and S&P gave Enron an investment-grade rating just a few days before its bankruptcy.

is associated with lenient credit ratings.

2.2.2 Informational effect of credit rating changes

Prior literature has investigated the information effect of credit rating changes (e.g., Holthausen and Leftwich 1986; Jorion, Liu, and Shi 2005). For example, using a sample of 637 rating changes across classes by Moody's and S&P, Holthausen and Leftwich (1986) find that downgrades are associated with negative abnormal stock returns in the two-day window beginning the day of the press release by the rating agency. Significant abnormal returns are associated with announcements of additions to the S&P’s Credit Watch List if either a potential downgrade or a potential upgrade is indicated. Jorion, Liu, and Shi (2005) investigate the informational effects of Regulation Fair Disclosure (Reg FD) on credit ratings. Because of Reg FD, credit analysts at rating agencies have access to confidential information that is no longer made available to equity analysts, potentially increasing the information content of credit ratings. They examine the effect of credit rating changes on stock prices and find that the informational effect of downgrades and upgrades is much greater in the post-Reg FD period. Xia (2014) examines the impact of the entry of an investor-paid CRA (the Egan-Jones Rating Company) on the information quality of S&P’s credit ratings. He finds that credit risk is incorporated more quickly, and the credit rating changes have higher information content after the entry of Egan-Jones Rating Company.

2.2.3 ESG performance and the cost of debt

Literature, in general, finds that firms with better ESG performance are associated with lower cost of debt (Goss and Roberts 2011; Ge and Liu 2015; Chang, Xu, and Yang 2020; Amiraslani, Lins, Servaes, and Tamayo 2022). Goss and Roberts (2011) examine the relationship between cost of bank loans and corporate social responsibility. They find that more socially responsible firms pay between 7 and 18 basis points less compared to firms with corporate social responsibility (CSR) concerns. Ge and Liu (2015) investigate the relationship between the cost of new bond issues and a firm's CSR performance and find that better CSR performance is associated with lower ex-ante cost of debt as proxied by credit ratings. Chang, Xu, and Yang (2020) investigate the impact of CSR on the debt market and find that better CSR performance is associated with a higher share of public debt to total debt. Amiraslani, Lins, Servaes, and Tamayo (2022) investigate whether bond pricing reflects the social capital as proxied by a firm's environmental and social performance and finds a relationship between social capital and bond spreads only during the 2008-2009 financial crisis and no relationship over the whole sample period 2006-2019.

2.2.4 ESG and credit ratings

There is an emerging literature that examines the intersection between ESG ratings and credit ratings. For example, Attig, El Ghoul, Guedhami, and Suh (2013) provide evidence that CRAs give firms higher credit ratings when they have good CSR performance, especially those that relate to employee relations and environmental performance. Jiraporn, Jiraporn, Boeprasert, and Chang (2014) find that firms with better CSR scores have better credit ratings. Jang, Kang, Lee, and Bae (2020) find that ESG scores can provide valuable information concerning the downside risk of firms, especially for smaller firms.

More closely related to our paper, there are a few papers that examine the use of ESG considerations by rating providers. For example, Kiesel and Lücke (2019) find that Moody's takes a small consideration of ESG in rating decisions during 2004-2015. They also find that ESG consideration predicts stock returns and CDS spread around the rating announcement. Bonacorsi, Cerasi, Galfrascoli, and Manera (2022) present evidence that ESG factors reduce the mean squared error that is incremental to accounting variables when explaining credit risk. Yang (2020) finds no evidence that the information quality of credit ratings improves after S&P and Moody's claim of having incorporated ESG starting in 2015 for the sample period of 2012-2019. We extend this stream of literature by shedding light on whether and how ESG information adds value to the traditional risk assessment of credit raters.

3. Data and sample

3.1. Data

Our financial data is from Compustat, stock price information is from CRSP, and credit rating information is from S&P Capital IQ database. Following the prior literature on credit ratings, we also exclude all firms in the financial industries and utilities industries given the unique regulatory environment these two industries face. We examine firm-years around the merger of S&P and RobecoSAM, which are the fiscal years between 2016 and 2023. This gives us roughly an equal number of firm-year observations in the pre- and post-merger window.

We obtain data on negative ESG incidents from RepRisk, which analyzes information from public sources and stakeholders, but intentionally excludes company self-disclosures. RepRisk's core research scope consists of 28 ESG issues. These 28 issues drive the entire research process, and every risk incident in RepRisk is linked to at least one of these issues. The issues were selected and defined in accordance with the key international standards related to ESG and business conduct (e.g., World Bank Group Environmental, Health, and Safety Guidelines, the IFC Performance Standards, the Equator Principles, the OECD Guidelines for Multinational Enterprises, the ILO Conventions, etc.). Some of the most common incidents in the Environmental category are those that have an impact on landscapes, ecosystems, and biodiversity, and on local pollution. In the Social category, the most common incidents involve impact on communities, and human rights abuses. Under Governance, the most common categories are Fraud, and other white-collar crimes.

We obtain S&P credit indicator reports that identify firms with varying levels of ESG credit factors from the S&P website. These credit factors are those that can materially influence the creditworthiness of a rated entity or issue and for which rating agencies have sufficient visibility and certainty to be included in credit rating analysis. S&P identifies and ranks E (Environmental), S (Social), or G (Governance) factors that are material for credit rating determination on a scale of 1 (the most positive consideration) to 5 (the most negative consideration). For example, AAR Corp. has scores of E-2, S-3, and G-2, which means they have moderately negative S related risk and neutral E and G related risks for credit rating purposes.

3.2. Descriptive statistics

Table 1 Panel A documents the sample selection process for our main tests. We start with the Compustat and CRSP merged sample between 2016-2023. We obtain firms' ESG ratings from S&P RobecoSAM. Next, we collect the long-term corporate credit rating data from S&P Capital IQ for our sample window and merge this with the Compustat firm-year sample. Following the prior literature, a numerical value is assigned to each rating on a notch basis starting with AAA as 1, AA+ as 2, AA as 3, etc. Since the Capital IQ database treats a credit rating corresponding to a rating action, we assign a firm's rating during the concurrent year equal to the firm's rating during the past rating action. We delete observations with a "D" (default) rating from S&P because this indicates that the firm is already in default and likely undergoing a restructuring. We also drop observations with missing bond credit ratings from S&P. We further drop observations with missing control variables. The final sample consists of 1,261 firms or 7,395 firm-year observations without missing information for variables of interest and control variables.

The main challenge with our identification is that S&P's merger with RobecoSAM would affect all rated entities. To address this challenge, we define the treatment group based on the availability of ESG ratings as of the merger date. Specifically, the treated firms are the group of firms with ESG ratings on the day of the Robeco acquisition, and the control firms are the group of firms without any ESG ratings on the day of the Robeco acquisition. So, the control firms may or may have not received an ESG rating after the acquisition. The treated group in our sample consists of 617 firms and the control group consists of 644 firms. Table 1 Panel B provides the industry composition of the sample firms. The sample firms are distributed across all the Fama-French 12 industries. Most notably, 13.2% of the sample are in the manufacturing industry; 17.1% of the sample are in the business equipment industry, and 19.1% of the firms belong to the other category that includes mines, construction, and building materials. The sample distribution suggests that we have a reasonable variation of industries in our sample.

Table 2 provides the summary statistics. The median credit rating has a numerical score of 12, which corresponds to a BB letter rating. The standard deviation of the credit rating is 3.163, with the first and third quartiles being 9 and 14, respectively. These statistics suggest that there is reasonable variation in credit quality over the sample period. The mean value of EDF is 0.058 with a median of 0 and standard deviation of 0.156. This is consistent with the Bharath and Shumway (2007) approximation of the Merton (1974)/KMV model. The average (median) firm has a total asset of $6.204 billion ($5.437 billion), which translates to logged values of 8.733 and 8.601. The mean (median) leverage ratio is 40.7% (37.8%) and the mean (median) profitability (measured as *EBITDA/Sales*) is 19.4% (16.5%).

4. Research design and results

4.1. Responsiveness of credit ratings to EDF

4.1.1. Baseline results

We investigate whether and how the information quality of credit rating changes when a credit rating agency provides ESG ratings to a credit rating client. We first examine the effect of S&P and RobecoSAM merger on the responsiveness of ratings to credit risk using the following difference-in-differences specification:

$$\boldsymbol{Rating_{i,t} = \alpha + \beta_1 EDF_{i,t} + \beta_2 Post_t{*}EDF_{i,t} + \beta_3 Treat_i{*}EDF_{i,t} + \beta_4 Treat_i{*}Post_t + \beta_5 Treat_i{*}Post_t{*}EDF_{i,t} + \sum \gamma_j Controls + Fixed\ Effects + \varepsilon_{i,t}} \quad \textbf{(1)}$$

Rating is the cardinal value of S&P's credit ratings from 1 (AAA) to 21 (C). *Treat* is an indicator that takes the value of 1 for firms that were already rated by RobecoSAM in the pre-merger period; 0 if not rated by RobecoSAM at the time of acquisition. *Post* is an indicator variable that takes the value of 1 for fiscal years that end between Feb 1, 2020, and December 31, 2023. *EDF*, which captures the probability that the firm value will fall below the value of debt (i.e., the probability of default over the next year), is the mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model. We use this measure because a number of studies show that the market-based Merton/KMV model provides an unbiased and informative credit risk measure and outperforms credit ratings from S&P and Moody's in tracking firms' fundamental credit risk (Bohn, Arora, and Korablev 2005; Korablev and Dwyer 2007).[6] Following Xia (2014), we first calculate

[6] Becker and Milbourn (2011), Cheng and Neamtiu (2009), Doherty, Kartasheva, and Phillips (2012), and Hertzberg, Liberti, and Paravisini (2010) examine the correlation between ratings and actual defaults as a measure of information quality of credit ratings. However, actual default during our short sample window is quite limited especially in the pre-merger period. Hence, we use EDF to proxy for default risk.

EDF on a firm-month basis and then average it over the firm-fiscal year to get a firm-year measure of EDF.[7]

The control variables used in our regression are a group of variables that prior research has found to be associated with the creditworthiness of the firm. We follow Baghai et al. (2014) in selecting these variables because the financial statement variables employed in that study are comprehensive with regard to prior literature, and are closely aligned with the variables employed in the rating process followed by Standard and Poor's (2008), and are well suited to analyses over a long time-series. They are: *Size* (log of total assets), *Profit* (EBITDA divided by sales), *Profitvol* (standard deviation of profit over the last five years, or at least the last two years if data is not available for the last five years), *Rent* (rental payments divided by total assets), *Debtcov* (ratio of long- and short-term debt to EBITDA),[8] *MTB* (market to book ratio), *Convdebt* (convertible debt divided by total assets), *Cash* (cash and short-term investments divided by total assets), *Intcov* (EBITDA divided by net interest paid), *Tangibility* (net property, plant, and equipment divided by total assets), and *Capex* (capital expenditures divided by total assets). We scale all of these variables by total assets to control for size differences across firms. All explanatory variables are winsorized at the 1st and 99th percentile to limit the influence of outliers. Finally, our main specification includes both firm fixed and year fixed effects to control for time-invariant firm attributes and macroeconomic factors that affect credit ratings over time. All variables are defined in Appendix A.

Table 3 Panel A provides the regression results from Equation (1). We start off with Column (1) that does not include any control variables, but includes just the industry and year

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[7] Xia (2014) uses a similar research design as ours to estimate credit quality of S&P credit ratings where EDF is calculated on a quarterly basis. Our results are robust to using quarterly EDF instead of averaging over a fiscal year.
[8] We set the ratio to zero when it is negative.

fixed effects. In Column (2), we add a set of control variables that are associated with the credit worthiness of the firm in addition to firm fixed effects. In Column (3), we add the interacted control variables that give us a fully specified model. The coefficient estimates on *Treat*Post*EDF* are positive and significant throughout the three columns, which confirms that S&P's ratings become more responsive to credit risk following the acquisition of RobecoSAM. For example, the coefficient estimates in Column (2) is 1.191 (t =2.614). This implies that a one standard deviation increases in *EDF* (0.156) is associated with 0.4 (i.e., calculated as (*1.191+1.443) *0.156*) notch downgrade in S&P credit ratings after the merger. This suggests a one-notch rating downgrade for approximately one out of three firms in the post-merger period. The 0.4 notch downgrade is comparable in size to the findings in Xia (2014) where he investigates how the information quality of issuer-paid S&P's credit ratings changes in response to the entry of the investor-paid rating agency Egan-Jones Rating Company. More specifically, Xia (2014) finds that *"… a one-standard-deviation (0.13) increase in the EDP is associated with 0.09-notch downgrade in S&P's ratings before EJR initiates coverage but with an approximately 0.3-notch downgrade after EJR's coverage initiation"*.

In addition, the positive coefficient estimate on *EDF* indicates that S&P's ratings are positively correlated to higher default risk and validates the EDF measure. This suggests that the information quality of S&P ratings has improved in the post-merger period. Collectively, the results in Panel A show that there is a meaningful increase in the ratings' association with *EDF* in the post-merger period. This is consistent with the informational quality of credit ratings increasing after the RobecoSAM acquisition.

4.1.2. Parallel trends

We test for any pre-trends in the data by estimating the dynamic analysis for the merger event following Bertrand and Mullainathan (2003). We start by replacing *Post* coefficient in Panel A with half-year dummy variables, since the merger announcement took place during the latter half of 2019. The results that use 2^{nd} half of 2018 (2018h2) as the base are presented in Panel B.

We find that the observed effect in Panel A starts after the RobecoSAM acquisition and persists until the sample period end. Specifically, the coefficient estimates on ratings quality are indistinguishable between treated and control group during the pre-period, and that there is an increase in ratings' association with EDF for the treatment group during the post-merger window. This confirms that the increase in the ratings' association with *EDF* is meaningful and occurs in the post RobecoSAM acquisition period.

4.2. Cross-sectional analyses

The results so far suggest that information quality of credit ratings increase after S&P's acquisition of the ESG ratings business. However, it may very well be the case that S&P has already incorporated this information in their credit ratings, and what we are documenting may be driven by unobserved factors that improve ratings quality for the treated entities. In order to further make the case that it is ESG information that is indeed increasing the credit ratings quality, we perform the following cross-sectional analyses.

4.2.1. Based on S&P's ESG credit indicator reports

We obtain information about the relevance of ESG factors to credit from S&P credit indicator reports. As described in Section 3, S&P identified ESG factors that can materially influence the creditworthiness of a rated entity from 1 through 5. The information channel would predict that in the post-merger period, the improvement in credit ratings quality is more likely to happen for firms with more positive or negative ESG factors that matter for credit rating determination. Further, given that credit rating agencies are concerned more about the downside risk of a firm, this effect will be stronger for those firms that have at least one negative ESG factor for credit ratings analysis.

The results are presented in Table 4 Panel A. In Columns (1) and (2), we separate the sample into firms that have at least one relevant ESG factors that goes into credit ratings vs. those firms where risk factors are neutral (score=2) or missing. In our sample, roughly one-third of the firm-year observations have either positive or negative ESG-relevant factors. Column (1) where we examine the group of firms that S&P deemed ESG to be relevant in credit ratings, the coefficient estimate on *Treat*Post*EDF* is 2.564 (t = 3.916). We note that this effect is almost twice the main effect on ratings quality documented in Table 3. In Column (2), we examine the group of firms for which ESG is not relevant, and find that the coefficient estimate on *Treat*Post*EDF* is 0.779 (t = 1.294). We find that the difference in coefficients across the two groups is statistically significant at the 1% level.

In Columns (3) and (4), we compare the firms with ESG factors that negatively impact credit ratings to the firms that have ESG factors that impact credit ratings in either a positive or neutral way. In Column (3) that examines the group of firms with ESG factors that negatively impact credit ratings, the coefficient estimate on *Treat*Post*EDF* is 2.710 (t = 3.922). In Column (4) that examines the group of firms that ESG factors do not negatively affect credit ratings, the coefficient estimate on *Treat*Post*EDF* is 0.724 (t = 1.207). We find that the difference in coefficients across the two groups is statistically significant at the 1% level. Overall, these results suggest that our main effect is consistent with ESG factors being incorporated into credit ratings in the post-merger period, and the improvement in quality comes from firms with more negative ESG factors.

4.2.2. Based on ESG risk

We examine whether ESG information helps credit ratings' relevance when a firm has higher ESG risk. Further, we are interested in understanding which among environmental, social, or governance (or all of these) risks are more likely to be of importance to credit rating agencies. We proxy for ESG risk, based on whether a firm experienced a negative ESG incident or not. This is from the RepRisk data. This analysis allows us to identify whether ESG information-fueled ratings improvement is more likely to happen among firms with higher ESG risk.

We separate our sample into two groups based on whether the firm experience any ESG related incidents or not. We note that the mean number of incidents in the *ESG Incidents* group is 5.8 compared to 0 news for the *No ESG Incidents* group. The results are presented in Table 4 Panel B. In Column (1), we examine the *ESG Incidents* group and find that the coefficient estimate on *Treat*Post*EDF* is 3.244 (t = 3.008). In Column (2), we examine the *No ESG Incidents* group and find that the coefficient estimate on *Treat*Post*EDF* is 0.576 (t = 1.051). The difference between the two groups is significant at the 1% level. We further dissect the negative ESG news into E (Columns (3)-(4)), S (Columns (5)-(6)), or G (Columns (7)-(8)), categories as identified in RepRisk. We find that our main effect is concentrated among firms with negative environmental and governance incidents. In sum, the results suggest that ESG information is more relevant to credit risk when a firm experiences a heightened ESG risk, especially relating to the environment and governance.

4.2.3. Based on information environment

We start by investigating the role of the firm-level ESG disclosure environment in shaping S&P's ability to process ESG information. As an increasing number of firms in the US voluntarily provide annual sustainability reports (Rouen et al. 2022), S&P may have already incorporated this information in their credit ratings even before the merger. Hence, such firms that make their sustainability reports available pre-merger would have a lower marginal improvement in the predictability of credit ratings post-merger. However, it may also happen that the ESG reports complement the existing research performed by S&P which could result in a further increase in S&P ratings quality. In order to test for this possibility, we obtain the data from Refinitiv about the firm-years in which ESG reports are available to capital market participants during the pre-merger period.

Based on the number of reports available each year, we separate the sample into firms that disclose ESG reports and firms that don't. *ESG Report* is an indicator variable that takes the value of 1 for firms that disclose ESG reports during the pre-merger year, and 0 otherwise

We report the results from Equation (1) across different groups in Table 4. In Column (1), we examine the group of firms without ESG reports and find that the coefficient estimate on *Treat*Post*EDF* is 0.923 (t = 1.668). In Column (2), we examine the group of firms that had ESG reports and find that the coefficient estimate on *Treat*Post*EDF* is 2.691 (t = 2.746). The difference between the two columns is significant at the 5% level. Overall, the results are consistent with the information channel from firm ESG reports driving our main results.

4.3. Additional analyses and robustness tests

4.3.1. Cumulative abnormal return as an alternative proxy for the information content

Next, we further provide evidence on increased information content after the RobecoSAM acquisition. Specifically, we use cumulative abnormal return as a proxy following the prior literature (e.g., Holthausen and Leftwich 1986; Hand, Holthausen and Leftwich 1992; Ederington and Goh 1998; Hull, Predescu and White 2004; Jorion, Liu and Shi 2005; Xia 2014). We measure the market reaction to credit ratings downgrades and upgrades using three-day cumulative abnormal returns (*CAR*) surrounding the downgrades (upgrades) including one day before the event, the event day (when S&P announces a rating change), and one day following the event. We use the following generalized event study specification to examine the market reaction surrounding downgrades for the treatment firm in the post period:

$$\boldsymbol{CAR_{i,t} = \alpha + \beta_1 Treat_i + \beta_2\, Post_t + \beta_3\, Treat_i * Post_t + \sum \gamma_j\, Controls + Fixed\ Effects + \varepsilon_{i,t}} \qquad \textbf{(2)}$$

where $CAR_{i,t}$ is the 3-day cumulative abnormal returns (in percentage) surrounding S&P's rating change announcements using the market model to calculate the daily abnormal returns. All other control variables are defined as in Equation (1). A greater market reaction would indicate that the changes in S&P's credit ratings contain more information that has not been impounded in the market, and accordingly, suggests that the ratings contain higher information content.

The results estimating Equation (2) are provided in Table 5. We first examine the downgrades in Panel A. Column (1) does not include any control variables and just includes year-month fixed effects, Column (2) adds a set of control variables that are associated with the creditworthiness of the firm used in Equation (1), and Column (3) further adds year-month and industry fixed effects.

Across all three columns, the coefficient estimates on *Treat*Post* are negative and statistically significant. For example, in Column (2), the coefficient estimate on *Treat*Post* is -0.077 (t = 2.392). This indicates that the market-reaction has become more negative in the post-merger period. Specifically, there is an additional negative abnormal reaction of 7.7 basis points for a one notch downgrade in credit ratings during the three-day window around the downgrade after the RobecoSAM acquisition. Overall, the results indicate that credit rating downgrades are more informative for treated firms in the post-merger period.

In Panel B, we examine rating upgrades instead of downgrades. We find evidence that the market-reaction has become more positive in the post-merger period. For example, in Column (2), the coefficient estimate on *Treat*Post* is 0.013 (t = 2.040). This suggests that there is an additional positive abnormal reaction of 1.3 basis points for a one notch upgrade in credit ratings during the three-day window around the upgrade after the RobecoSAM acquisition. To summarize, both measures of S&P's ratings quality (*EDF* and *3-day CAR*) suggest that the availability of ESG information used to generate ESG ratings in the post-merger period has increased S&P's responsiveness to credit risk and the information content of S&P's ratings.

4.3.2. Matching

In this subsection, we use the entropy-balanced matching technique to match treatment and control observations based on observable firm characteristics to alleviate endogeneity concerns (Hainmueller, 2012; McMullin and Schonberger, 2020; Basu et al., 2022). The entropy-balanced matching approach provides a way to reduce this noise that would otherwise be present in our estimation if the average treatment observation is not sufficiently comparable to the average control observation. The entropy balancing technique preserves the full sample and ensures covariate balance between treatment and control observations by re-weighting observations such that the post-weighting mean and variance for treatment and control observations are virtually identical along with credit rating controls. This approach ensures that our treatment and control samples are comparable based on observable firm characteristics, thus allowing us to reasonably identify information quality changes of credit ratings as a response to the information transfer instead of the inherent and unobservable differences in firm characteristics across the treatment and the control sample.

We carry out entropy matching using a comprehensive set of firm characteristics during the pre-merger period, as the goal of this empirical strategy is to mitigate differences across observations in the treatment and the control groups. The specific covariates used in entropy balanced matching are *Size, Leverage, Capex, Tangibility, Cash, Intcov, Debtcov, Convdebt, EDF,* and *Rating*. Appendix Table 1 Panel A first provides the mean and variance of each variable across our treatment and control subsamples before we employ entropy matching. Pre-matching, there are some significant differences between the two groups of observations. For example, the treated group is much bigger than the control group (the mean average size is 9.526 for the treated group compared with 7.776 for the control group). The treated group has lower leverage, lower level of tangible assets, higher interest coverage ratio. Also, the treated group have better credit ratings (the mean average credit rating of 10.04 for the treated group compared with 13.79 for the control group). Post-matching, there are no notable differences in either the mean or variance of any of the matching variables across the two groups.

Panel B provides the matched sample results from Equation (1) for the responsiveness of ratings to EDF and Panel C (D) provides the robustness results from Equation (2) for the market reaction. Across the three panels, we generally find results consistent with those presented in

Tables 3-5. Overall, the results suggest that credit ratings are becoming more informative after the RobecoSAM acquisition.

4.3.3. Additional tests on the role of information

In this sub-section, we conduct additional tests to highlight the role of information. We compare different groups of firms affected differently by the RobecoSAM acquisition. We identify four potential groups. The first group (i.e., Group 1) is the group of firms that had RobecoSAM ESG coverage before the acquisition and continue to have an ESG rating after the acquisition. This is the treated group in our main analysis throughout the draft so far. For these group of firms, S&P would likely have experienced an increase in the available information relevant for credit ratings (i.e., direct and firm specific information) after the RobecoSAM acquisition. In addition, the awareness towards the importance of ESG would have increased for the S&P analysts that cover these firms.

The second group (i.e., Group 2) is the group of firms that did not have RobecoSAM coverage before the acquisition, but had an ESG rating after the acquisition. For these group of firms, S&P would likely have experienced an increase in the available information relevant for credit ratings (e.g., industry related information) after the RobecoSAM acquisition, but less so than Group 1. The awareness towards the importance of ESG would have also increased for the S&P analysts that cover these firms similar.

The third group (i.e., Group 3) is the group of firms that did not have RobecoSAM coverage before the acquisition and continued to not have ESG ratings after the acquisition. These group of firms would not have benefitted from any potential information nor awareness from the RobecoSAM acquisition. The fourth group (i.e., Group 4) is the group of firms that had

RobecoSAM coverage before the acquisition, but no longer have ESG ratings after the acquisitions. We note that there are no such firms in our sample.

In Appendix Table 2, we present results comparing the different groups to each other. In Column (1), we compare Group 1 to Group 3. We find that *Treat*Post*EDF* is positive and significant. This suggests that there is a meaningful increase in information as well as awareness towards ESG information after the RobecoSAM acquisition. In Column (2), we compare Group 2 to Group 3. We find that *Treat*Post*EDF* is positive and significant. This suggests that there is a meaningful increase in awareness towards ESG information after the RobecoSAM acquisition. In Column (3), we compare Group 1 and 2 to Group 3. We find that *Treat*Post*EDF* is positive and significant. As in Column (1), this suggests that there is a meaningful increase in information as well as awareness towards ESG information after the RobecoSAM acquisition. In Column (4), we compare Group 1 to Group 2. We find that *Treat*Post*EDF* is positive and significant. This means that Group 1, there is a meaningful role that firm specific ESG information is playing in making credit ratings more relevant.

5. Conclusion

We investigate whether and how the information quality of credit rating changes when a credit rating agency provides ESG ratings to a credit rating client. Using two related measures of ratings quality, namely, the responsiveness of ratings to credit risk and the information content of rating changes, we document that the information quality of S&P's credit ratings improves after acquiring an ESG ratings provider: RobecoSAM. Specifically, the credit ratings become more responsive to credit risk, especially among the firms that RobecoSAM covered ex-ante, and this effect is driven by firms with weaker information environments (e.g., without ESG reports and lower analyst coverage). Further, we find evidence that S&P's credit rating changes contain more information that has not been impounded in the market after the acquisition.

Our study contributes to a few areas of the literature. First, we contribute to the literature that examines the information content of credit ratings by documenting that credit rating has better information content when the CRA also provides ESG credit ratings. Second, we also contribute to the literature that examines the intersection of ESG and credit ratings by showing that ESG information adds value to the traditional risk assessment of credit raters. Finally, we extend the recent literature that examines ESG risk by showing that ESG signals can improve the usefulness and information quality of credit ratings.

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Table 1. Sample

Panel A. Sample selection for estimated default probability tests

	Firm-Year
Compustat and CRSP merged sample (2016-2023)	33,637
Less: Missing S&P firm credit ratings	(24,196)
Less: Financial and utilities firms	(1,127)
Less: Missing Compustat control variables & singleton observations	(919)
Final sample	7,395

Panel B. Breakdown of the sample of firms using the Fama-French industry classification

Fama-French Industry	*# Firms*	*% Firms*
Consumer Non-Durables -- Food, Tobacco	84	6.7%
Consumer Durables -- Cars, TV's, Furniture	43	3.4%
Manufacturing -- Machinery, Trucks, Plant	166	13.2%
Oil, Gas, and Coal Extraction and Products	139	11.0%
Chemicals and Allied Products	62	4.9%
Business Equipment - Computers, Software	216	17.1%
Telephone and Television Transmission	62	4.9%
Wholesale, Retail, and Some Services	155	12.3%
Healthcare, Medical Equipment, and Drug	93	7.4%
Other	241	19.1%
Total	1,261	100

Table 2. Descriptive statistics

This table presents the descriptive statistics of the variables used in the regression analyses. *Rating* is the cardinal value of S&P's credit ratings from 1 (AAA) to 21 (C). *EDF* is the mean of the monthly expected default probability in the past year (12 months). *3-day CAR(Downgrades and Upgrades)* is the three-day cumulative adjusted returns surrounding calculated based on the adjusted market model. *Size* is the log of assets. *Profit* is EBITDA over sales and *Profitvol* is standard deviation of profit over the last five years, or at least the last two years if insufficient data. *Rent* is rental payments divided by assets, measured at the end of fiscal year. *Leverage* is sum of long-term debt and debt in current liabilities scaled by assets. *Cash* is cash and short-term investments scaled by assets measured at the end of fiscal year. *MTB* is ratio of market value of equity divided by book value of equity. *Capex* is capital expenditures over assets. *Tangibility* is net property, plant, and equipment over assets. *Intcov* is EBITDA over net interest paid. *Debtcov* is EBITDA over net interest paid, or zero if ratio is negative for fiscal year. All variables are defined in Appendix A.

	Mean	Std. Dev.	P25	Median	P75
Dependent Variables:					
Credit Rating	11.671	3.163	9	12	14
EDF	0.058	0.156	0	0	0.013
3-day CAR (Downgrades)	-0.017	0.132	-0.055	-0.008	0.029
3-day CAR (Upgrades)	0.004	0.050	-0.022	0.002	0.026
Rating Control Variables:					
Size	8.733	1.452	7.676	8.601	9.665
Profit	0.194	0.157	0.101	0.165	0.261
Profitvol	0.121	0.198	0.009	0.022	0.079
Rent	0.018	0.03	0.004	0.	0.018
Leverage	0.407	0.209	0.265	0.378	0.516
Cash	0.1	0.098	0.03	0.07	0.138
MTB	3.285	8.665	1.124	2.141	4.079
Capex	0.043	0.047	0.015	0.029	0.053
Tangibility	0.303	0.254	0.096	0.212	0.468
Intcov	22.275	57.945	3.93	7.617	14.233
Debtcov	4.255	4.659	1.936	3.224	4.962

Table 3. Responsiveness of S&P ratings to expected default frequency

Panel A. Baseline results

Panel A reports the firm-fixed-effect OLS regression results on the responsiveness of S&P ratings to Expected Default Frequency. *Rating* is the cardinal value of S&P's credit ratings from 1 (AAA) to 21 (C). *Treat* is a dummy variable that equals one if a firm has received an ESG score before the merger event (i.e., before November 2019), and zero otherwise. *Post* is a dummy variable that equals one for the firm-years after the merger completion (i.e., Feb 2020), and zero otherwise. *EDF* is the mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model. Panel B reports the parallel trends tests for the responsiveness of S&P ratings to Expected Default Frequency on a half-year basis. 2018h2 is used as the baseline year. All other variables are defined in Appendix A. The sample consists of firm-year observations of 1,261 firms that are rated by S&P during our sample period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, using two-tailed tests and standard errors double clustered by firm and year-month.

	(1)	(2)	(3)
		Credit Rating	
*Treat*Post*EDF*	2.954***	1.191**	1.263***
	(2.667)	(2.614)	(2.827)
*Treat*Post*	-0.096*	-0.084	-0.042
	(-1.723)	(-1.185)	(-0.492)
*Treat*EDF*	0.702	0.253	0.200
	(0.669)	(0.823)	(0.635)
*Post*EDF*	-1.187***	-0.020	-0.162
	(-2.875)	(-0.078)	(-0.596)
Treat	-3.339***		
	(-24.683)		
EDF	5.744***	1.443***	1.517***
	(15.317)	(6.035)	(6.313)
Control Variables	No	Yes	Yes
Control Interaction	No	No	Yes
Fixed Effects	Industry & Year-month	Firm & Year-month	Firm & Year-month
Observations	7,395	7,395	7,395
R-squared	0.503	0.959	0.959

Panel B. Parallel trends

	(1)
	Credit Rating
*Treat*2016h1*EDF*	2.667
	(1.465)
*Treat*2016h2*EDF*	0.248
	(0.554)
*Treat*2017h1*EDF*	-1.651
	(-0.616)
*Treat*2017h2*EDF*	0.403
	(0.897)
*Treat*2018h1*EDF*	0.452
	(0.590)
*Treat*2019h1*EDF*	1.184
	(1.310)
*Treat*2019h2*EDF*	1.229**
	(2.272)
*Treat*2020h1*EDF*	2.864***
	(3.134)
*Treat*2020h2*EDF*	2.016***
	(5.636)
*Treat*2021h1*EDF*	6.284***
	(3.533)
*Treat*2021h2*EDF*	2.085**
	(2.133)
*Treat*2022h1*EDF*	3.369*
	(1.679)
*Treat*2022h2*EDF*	0.491
	(0.820)
*Treat*2023h1*EDF*	2.974**
	(2.380)
*Treat*2023h2*EDF*	1.648***
	(4.382)
Control Variables	Yes
Interacted Variables	Yes
Fixed Effects	Firm and Year-month
Observations	7,395
R-squared	0.960

Table 4. Cross-sectional tests

Panel A. Based on S&P's ESG credit indicator reports

Panel A reports the effect on improvement in ratings quality for *ESG Relevant* issuers. *Rating* is the cardinal value of S&P's credit ratings from 1 (AAA) to 21 (C). *Treat* is a dummy variable that equals one if a firm has received an ESG score before the merger event (i.e., before November 2019), and zero otherwise. *Post* is a dummy variable that equals one for the firm-years after the merger completion (i.e., Feb 2020), and zero otherwise. *EDF* is the mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model. *ESG Relevant (Negative ESG Relevant)* is a dummy identifying firms with at least one ESG relevant (Negative ESG relevant) factors as identified by S&P post-merger. Panel B panel reports the effect on improvement in ratings quality based on firm ESG risk. *ESG Incidents* is a dummy identifying firms with at least one negative incident as identified by RepRisk in a particular year. All variables are defined in Appendix A. The sample consists of firm-year observations of 1,261 firms that are rated by S&P during our sample period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, using two-tailed tests and standard errors double clustered by firm and year-month.

	(1)	(2)	(3)	(4)
	Credit Rating			
	ESG Relevant=1	*ESG Relevant=0*	*Negative ESG Relevant=1*	*Negative ESG Relevant=0*
*Treat*Post*EDF*	2.564***	0.779	2.710***	0.724
	(3.916)	(1.294)	(3.922)	(1.207)
	p-value of the difference			
	0.000		*0.000*	
*Treat*Post*	-0.057	-0.065	-0.064	-0.064
	(-0.341)	(-0.679)	(-0.380)	(-0.694)
*Treat*EDF*	-1.372***	0.692	-1.509***	0.710
	(-3.003)	(1.408)	(-3.022)	(1.440)
*Post*EDF*	-0.616	-0.131	-0.752	-0.111
	(-1.152)	(-0.416)	(-1.328)	(-0.355)
EDF	2.600***	1.336***	2.683***	1.325***
	(5.483)	(5.447)	(5.408)	(5.408)
Control Variables	Yes			
Fixed Effects	Firm & Year-month			
Observations	2,028	5,331	1,752	5,612
R-squared	0.964	0.958	0.957	0.962

Panel B. Based on the firms' ESG risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Credit Rating							
	ESG Incidents =1	*ESG Incidents =0*	*E Incidents =1*	*E Incidents =0*	*S Incidents =1*	*S Incidents =0*	*G Incidents =1*	*G Incidents =0*
*Treat*Post*EDF*	3.244***	0.576	6.863***	0.825*	2.908	0.735	3.266***	0.802*
	(3.008)	(1.051)	(3.069)	(1.820)	(1.606)	(1.453)	(2.688)	(1.675)
	p-value of the difference							
	0.010		*0.000*		*0.210*		*0.040*	
*Treat*Post*	-0.268*	0.072	-0.346	-0.001	-0.164	0.014	-0.476**	0.063
	(-1.816)	(0.678)	(-1.358)	(-0.014)	(-0.999)	(0.147)	(-2.117)	(0.689)
*Treat*EDF*	-1.759*	0.405	-4.017*	0.370	-2.257	0.438	-1.525	0.287
	(-1.747)	(0.959)	(-1.823)	(1.086)	(-1.316)	(1.113)	(-1.230)	(0.802)
*Post*EDF*	-0.716	-0.002	-1.957	-0.080	-0.758	-0.073	-0.882	-0.033
	(-0.977)	(-0.008)	(-0.951)	(-0.296)	(-0.477)	(-0.279)	(-1.049)	(-0.119)
EDF	2.566***	1.447***	3.855*	1.471***	3.316*	1.436***	2.532**	1.453***
	(2.813)	(5.917)	(1.875)	(6.781)	(1.976)	(6.299)	(2.233)	(6.312)
Control Variables	Yes							
Control Interaction	Yes							
Fixed Effects	Firm & Year-month							
Observations	2,475	4,919	1,179	6,195	1,900	5,495	1,616	5,771
R-squared	0.956	0.956	0.961	0.957	0.957	0.957	0.956	0.957

Table 5. Cross-sectional tests based on firm's information environment

This table reports the cross-sectional results on the responsiveness of S&P ratings to Expected Default Frequency (Panel A). *Rating* is the cardinal value of S&P's credit ratings from 1 (AAA) to 21 (C). *Treat* is a dummy variable that equals one if a firm has received an ESG score before the merger event (i.e., before November 2019), and zero otherwise. *Post* is a dummy variable that equals one for the firm-years after the merger completion (i.e., Feb 2020), and zero otherwise. *EDF* is the mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model. *ESG Reports* is a dummy identifying firms that disclose ESG reports during the year before the merger event. All variables are defined in Appendix A. The sample consists of firm-year observations of 1,050 firms that are rated by S&P as of November 2019. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, using two-tailed tests and standard errors double clustered by firm and year-month.

	(1)	(2)
	ESG Reports=0	*ESG Reports=1*
*Treat*Post*EDF*	0.923*	2.691***
	(1.668)	(2.746)
	p-value of the difference	
	0.000	
*Treat*Post*	0.012	-0.254
	(0.118)	(-1.359)
*Treat*EDF*	0.204	-0.736
	(0.433)	(-0.894)
*Post*EDF*	-0.062	-0.193
	(-0.203)	(-0.220)
EDF	1.547***	1.699**
	(5.706)	(2.344)
Control Variables	Yes	Yes
Control Interaction	Yes	Yes
Fixed Effects	Firm & Year-month	
Observations	5,500	1,889
R-squared	0.954	0.958

Table 6. Information content of S&P ratings changes

Panel A (B) presents the three-day cumulative abnormal returns (in percentage) surrounding S&P's rating downgrades (upgrades). *3-day CAR* is the three-day cumulative adjusted returns calculated based on the adjusted market model. *Treat* is a dummy variable that equals one if a firm has received an ESG score before the merger event (i.e., before November 2019), and zero otherwise. *Post* is a dummy variable that equals one for the firm-years after the merger completion (i.e., Feb 2020), and zero otherwise. *EDF* is the mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model. All other variables are defined in Appendix A. The sample consists of 804 downgrade and 756 upgrade events during our sample period (2016-2023) for the1,261 firms that are rated by S&P during our sample period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, using two-tailed tests and standard errors double clustered by firm and year-month.

Panel A. Downgrades

	(1)	(2)	(3)
	3-day CAR		
*Treat*Post*	-0.075**	-0.077**	-0.080**
	(-2.399)	(-2.392)	(-2.348)
Treat	0.046***	0.045***	0.046**
	(3.137)	(2.848)	(2.528)
Control Variables	No	Yes	Yes
Fixed Effects	Year-month		Industry & Year-month
Observations	804	804	804
R-squared	0.112	0.120	0.173

Panel B. Upgrades

	(1)	(2)	(3)
	3-day CAR		
*Treat*Post*	0.012*	0.013**	0.010*
	(1.940)	(2.040)	(1.771)
Treat	-0.004	0.000	0.004
	(-0.887)	(0.079)	(0.602)
Control Variables	No	Yes	Yes
Fixed Effects	Year-month		Industry & Year-month
Observations	756	756	756
R-squared	0.156	0.170	0.242

Appendix A. Variable definitions

Variable	Description	Data Source
Panel A: Dependent Variables		
Rating	Standard & Poor's Domestic Long-Term Issuer Credit Rating (SPLTICRM) as of the fiscal year end t, translated into a numerical scale by adding one for each rating notch. Thus, a AAA rating becomes 1, AA+ becomes 2, AA becomes 3, etc., up to a score of 21 for a rating of C.	WRDS
EDF	Mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model.	Constructed
3-day CAR	3-day cumulative abnormal returns (in percentage) surrounding S&P's rating downgrade (upgrade) announcements.	Constructed
Panel B: Firm-Level Determinants of Corporate Credit Rating		
Cash	Cash and short-term investments (CHE) scaled by assets (AT), measured at the end of fiscal year *t*.	Compustat
Rent	Rental payments (XRENT) divided by assets (AT), measured at the end of fiscal year *t*.	Compustat
Convdebt	Convertible debt divided by assets (AT).	Compustat
Intcov	EBITDA (OIBDP) over net interest paid (INTPN).	Compustat
Size	Log of assets (AT).	Compustat
Tangibility	Net property, plant, and equipment (PPENT) over assets (AT).	Compustat
CAPEX	Capital expenditures (CAPX) over assets (AT).	Compustat
Profit	EBITDA (OIBDP) over sales (SALE).	Compustat
Profitvol	Standard deviation of PROFIT over the last five years, or at least the last two years if insufficient data.	Compustat
Debtcov	EBITDA (OIBDP) over net interest paid (INTPN), or zero if ratio is negative for fiscal year *t*.	Compustat
NegDebtcov	A dummy variable that equals one if DEBTCOV is negative.	Compustat
Panel C: Other		
Treat	A dummy variable that equals one if a firm has received an ESG score before the merger announcement (i.e., before November 2019), and zero otherwise.	
Post	A dummy variable that equals one for the firm-years after the merger completion (i.e., Feb 2020), and zero otherwise.	Constructed

Appendix B. Example of ESG relevant factors for credit ratings from S&P

This table shows an excerpt from S&P's report on ESG credit indicators for the global aerospace and defense sector (https://www.spglobal.com/ratings/en/research/pdf-articles/211213-esg-credit-indicator-report-card-aerospace-and-defense). ESG credit indicators provide additional disclosure and transparency at the entity level and reflect S&P's opinion of how material the influence (on a 1-5 scale) of environmental, social, and governance factors have on credit rating analysis. An ESG credit indicator of E-2, S-2, or G-2 means that it is currently a neutral consideration for credit rating analysis.

ESG Credit Indicators By Issuer For North America

	Credit indicator			
Issuer	**E**	**S**	**G**	**ESG credit factors**
AAR Corp.	E-2	S-3	G-2	Health and safety
ADS Tactical Inc.	E-2	S-2	G-2	N/A
Advanced Integration Technology L.P.	E-2	S-3	G-2	Health and safety
Aerojet Rocketdyne Holdings Inc.	E-2	S-2	G-2	N/A
Amentum Holdings LLC	E-2	S-2	G-3	Governance structure
API Holdings III Corp.	E-2	S-2	G-3	Governance structure
Arcline FM Holdings LLC	E-2	S-2	G-3	Governance structure
Boeing Co.	E-2	S-5	G-4	Health and safety; Risk management, culture, and oversight; Transparency and reporting; Governance structure
Bombardier Inc.	E2	S3	G3	Health and safety; Governance structure
Booz Allen Hamilton Inc.	E-2	S-2	G-2	N/A
BWX Technologies Inc.	E-2	S-2	G-2	N/A
CACI International Inc.	E-2	S-2	G-2	N/A
CPI International Inc.	E-2	S-3	G-3	Governance structure
Ducommun Inc.	E-2	S-3	G-2	Health and safety
Dynasty Acquisition Co. Inc.	E-2	S-4	G-3	Health and safety; Governance structure
Forming Machining Industries Holdings LLC	E-2	S-5	G-3	Health and safety; Governance structure
General Dynamics Corp.	E-2	S-2	G-1	Risk management, culture, and oversight

Appendix Table 1. Key results after entropy balanced matching

This table reports the matched sample analysis results from Tables 3 and 4. Panel A reports the comparisons of mean and variance for various firm characteristics (i.e., firm-level determinants of corporate credit rating) between the treatment and control firms, pre- and post- entropy balanced matching. *Size* is the log of assets. *Leverage* is sum of long-term debt and debt in current liabilities scaled by assets. *Cash* is cash and short-term investments scaled by assets measured at the end of fiscal year. *Capex* is capital expenditures over assets. *Tangibility* is net property, plant, and equipment over assets. *Intcov* is EBITDA over net interest paid. *Debtcov* is EBITDA over net interest paid, or zero if ratio is negative for fiscal year. Panel B reports the result on the responsiveness of S&P ratings to Expected Default Frequency (*EDF*). Panel C reports the three-day cumulative abnormal returns (in percentage) surrounding S&P's rating downgrade (Panel B). *Rating* is the cardinal value of S&P's credit ratings from 1 (AAA) to 21 (C). *3-day CAR* is the three-day cumulative adjusted returns calculated based on the adjusted market model. *Treat* is a dummy variable that equals one if a firm has received an ESG score before the merger event (i.e., before November 2019), and zero otherwise. *Post* is a dummy variable that equals one for the firm-years after the merger completion (i.e., Feb 2020), and zero otherwise. *EDF* is the mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model. All variables are defined in Appendix A. The sample consists of firm-year observations of 1,050 firms that are rated by S&P as of November 2019. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, using two-tailed tests and standard errors double clustered by firm and year-month.

Panel A. Covariate balance

	Pre-Matching				Post-Matching			
	Treatment Mean	Control Mean	Treatment SD	Control SD	Treatment Mean	Control Mean	Treatment SD	Control SD
Size	9.526	7.776	1.274	1.017	9.526	9.526	1.274	1.274
Leverage	0.640	0.707	0.186	0.250	0.64	0.64	0.186	0.186
Capex	0.04	0.048	0.036	0.059	0.04	0.04	0.036	0.036
Tangibility	0.286	0.344	0.236	0.288	0.286	0.286	0.236	0.236
Cash	0.106	0.089	0.095	0.093	0.106	0.106	0.095	0.095
Intcov	25.3	19.07	57.827	58.344	25.3	25.3	57.827	57.827
Debtcov	3.203	4.628	2.321	4.177	3.203	3.203	2.321	2.321
EDF	2.102	8.471	8.762	17.085	2.102	2.103	8.762	8.766
Rating	10.04	13.790	2.786	2.281	10.040	10.040	2.786	2.786

Panel B. Responsiveness of S&P ratings to expected default frequency

	(1)	(2)	(3)
	Credit Rating		
*Treat*Post*EDF*	7.944***	1.666***	1.742***
	(4.174)	(3.153)	(3.482)
*Treat*Post*	-0.004	0.069	0.123
	(-0.016)	(0.748)	(1.303)
*Treat*EDF*	-2.110*	-0.193	-0.248
	(-1.766)	(-0.489)	(-0.641)
*Post*EDF*	-6.363***	-0.552	-0.730
	(-2.950)	(-1.121)	(-1.449)
Treat	-1.321***		
	(-4.060)		
EDF	9.209***	1.785***	1.887***
	(8.713)	(3.658)	(3.759)
Controls	Yes	Yes	Yes
Control Interaction	No	No	Yes
Fixed Effects	Industry & Year-month	Firm & Year-month	
Observations	7,395	7,395	7,395
R-squared	0.277	0.957	0.958

Panel C. Three-day cumulative abnormal returns for downgrades

	(1)	(2)	(3)
		3-day CAR	
*Treat*Post*	-0.057*	-0.061**	-0.071**
	(-1.945)	(-2.147)	(-2.484)
Treat	0.031***	0.032**	0.040***
	(2.738)	(2.494)	(2.655)
Controls	No	Yes	Yes
Fixed Effects	Year-month	Year-month	Industry & Year-month
Observations	804	804	804
R-squared	0.087	0.111	0.170

Panel D. Three-day cumulative abnormal returns for upgrades

	(1)	(2)	(3)
		3-day CAR	
*Treat*Post*	0.016**	0.016**	0.017**
	(2.231)	(2.216)	(2.450)
Treat	-0.006	-0.004	-0.004
	(-1.011)	(-0.648)	(-0.729)
	0.016**	0.016**	0.017**
Controls	No	Yes	Yes
Fixed Effects	Year-month	Year-month	Industry & Year-month
Observations	756	756	756
R-squared	0.169	0.184	0.262

Appendix Table 2. Additional tests on the role of information

This table reports the effect of information vs awareness channel. The entire sample is divided into 3 groups. Group 1 consists of firms with ESG ratings available at the merger date and that continued to have ESG ratings after the merger. Group 2 consist of firms who did not have ESG ratings at merger date but obtained ratings after the merger. Group 3 consists of firms who did not have an ESG ratings during our sample period, both in pre and post the merger. *Rating* is the cardinal value of S&P's credit ratings from 1 (AAA) to 21 (C). *Treat* is a dummy variable that equals one if a firm has received an ESG score before the merger event (i.e., before November 2019), and zero otherwise. *Post* is a dummy variable that equals one for the firm-years after the merger completion (i.e., Feb 2020), and zero otherwise. *EDF* is the mean of the monthly expected default probability in the past year (12 months) where the expected default frequency is derived from the Merton/KMV model. All variables are defined in Appendix A. The sample consists of firm-year observations of 1,261 firms that are rated by S&P during our sample period. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively, using two-tailed tests and standard errors double clustered by firm and year-month.

	(1)	(2)	(3)	(4)
	Group 1 vs. Group 3	Group 2 vs. Group 3	Group 1 + 2 vs. Group 3	Group 1 vs. Group 2
		Credit Rating		
*Treat*Post*EDF*	2.344***	1.586**	1.808***	1.025**
	(4.322)	(2.510)	(3.295)	(2.025)
*Treat*Post*	-0.083	-0.060	-0.074	-0.030
	(-0.383)	(-0.284)	(-0.371)	(-0.352)
*Treat*EDF*	-0.073	-0.531	-0.346	0.336
	(-0.161)	(-0.789)	(-0.616)	(0.798)
*Post*EDF*	-1.297***	-1.380***	-1.339***	0.086
	(-2.753)	(-2.961)	(-2.764)	(0.243)
EDF	1.761***	1.878***	1.813***	1.344***
	(4.080)	(4.656)	(4.273)	(3.667)
Control Variables	Yes	Yes	Yes	Yes
Control Interaction	Yes	Yes	Yes	Yes
Fixed Effects			Firm & Year-month	
Observations	4,613	3,321	7,395	6,843
R-squared	0.963	0.910	0.959	0.957