Credit Ratings in the Age of Environmental, Social, and Governance (ESG)

RUOKE YANG*

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Abstract

I present the first study that systematically examines the implications of ESG adoption by credit rating agencies. I find that, with a recent emphasis by Standard & Poor's and Moody's on incorporating ESG issues into their analysis, credit ratings positively reflect firms with lower carbon emissions and better social ratings. Despite the enhanced recognition of such issues by credit rating agencies, standard tests reveal no consistent evidence of improvement in the informational quality of credit ratings. This is concerning and suggests a cautious interpretation of the raters' stated purpose of ESG adoption, which aims to enhance their assessment of credit risk.

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*Yang (corresponding author) is with the U.S. Securities and Exchange Commission. E-mail: ruoke.yang@gmail.com. Mailing Address: 100 F Street, NE Washington, DC 20549. I thank Franklin Allen, Patrick Bolton, Charles Calomiris, Claudia Custodio, Chris Hansman, Raj Iyer, Marcin Kacperczyk, Harry Mamaysky, Alex Michaelides, David Miles, Ramana Nanda, Savi Sundaresan, Harry Turtle, and Sunil Wahal for their insightful comments and thoughtful suggestions. This paper was initially released prior to the author joining the Commission. The Securities and Exchange Commission disclaims responsibility for any private publication or statement of any SEC employee or Commissioner. This article expresses the author's views and does not necessarily reflect those of the Commission, the Commissioners, or members of the staff.

1. Introduction

Credit ratings serve a vital function in debt markets by providing signals to the investing public about the creditworthiness of borrowers. In disseminating this information widely in a standard format, credit rating agencies make easily accessible to the market their financial expertise and, in doing so, reduce the duplication of effort by other market participants. For most of their century-long history, these watchdogs have done just that.

With environmental, social, and governance (ESG) issues coming to the fore in the financial world, credit rating agencies have not stood idly by and have, in recent years, openly expressed their commitment to factoring these issues into their analysis. For instance, according to Moody's, problems with ESG are cited as 'material in one-third of Moody's private-sector rating actions' in 2019.[1] Behind this move is the belief that integrating ESG into their practices helps them better understand financial risk (S&P 2015; Moody's 2015). This is noteworthy as interest in ESG issues (e.g pollution, land degradation, child labor) have historically been driven by social preferences and concern for the well-being of stakeholders.

In this paper, I conduct the first investigation into the effect of this emphasis towards ESG (hereafter referred to as 'ESG adoption') in the credit ratings business. As credit rating agencies have signaled their commitment to embracing ESG, have credit ratings become, on average, more driven by information signals pertaining to ESG? If so, is there consistent evidence from standard tests used in the literature that the informational quality of these credit ratings improved?

Despite the stated intentions from the credit rating agencies about their reason for factoring ESG into their analysis, it is not obvious what the answers are to these questions. It could be that ESG issues in and of themselves are genuinely relevant to credit risk, and by properly understanding ESG issues, credit rating agencies arrive at a more nuanced understanding of the securities that they are rating. For instance, analysis of ESG issues can offer fresh insights into risks, ranging from reputational to legal to market, that could jeopardize the firm's ability to generate revenue or obtain funding. In

[1] https://esg.moodys.io/ Last accessed April 18, 2020.

the age of ESG, there is a growing body of investors and consumers, in conjunction with regulators, who may eschew, or in some cases, punish businesses that are viewed as heavy polluters or are involved in poor labor practices.[2] Under this scenario, adopting ESG in their ratings evaluation should result in an increase in the informational value of credit ratings, which should more strongly reflect ESG issues. On the other hand, there may be no additional effect from ESG adoption on credit ratings as the whole affair could be mostly a continuation of existing practices reframed in a public relations effort on the part of the credit rating agencies in response to public interest about ESG. It is not clear to what extent ESG adoption is about emphasizing the 'E' and the 'S', as opposed to a rebranding of the 'G', which has traditionally mattered for credit ratings. In this case, the 'adoption' of ESG in the credit ratings business does little to enhance the informational value of these ratings given that there are no significant alterations to the ratings process.

It is also conceivable that the emphasis of ESG in credit ratings analysis is less useful than originally thought (due in no small part to its potential informational quality benefits being 'netted out' by substantial ESG data quality problems as shown in Yang (2022) and Daines, Gow, and Larcker (2010)). That is, although credit rating agencies contend that incorporating ESG issues makes their ratings more informative about credit risk, there is no independent evidence to suggest that doing so translates into a marked increase in the ability for these credit ratings to predict future default, which is the main purpose of credit ratings. Therefore, it is possible that ESG signals do become important to the determination of credit ratings while generating no detectable or consistent improvement to the informativeness of credit ratings. This scenario with credit rating agencies can be benign from the standpoint of investors who rely on ratings that may not necessarily worse off in terms of informational quality. However, the implications for firms can be potentially quite detrimental if some are penalized in ratings about their creditworthiness through a policy that does not reliably benefit the quality of such assessments.

To explore how the credit ratings business has evolved in the age of ESG, I turn to the emphasis of ESG in the credit ratings business announced by Standard and Poor's (S&P) and Moody's in late

[2]Within the framework laid out in Merton (1974), including ESG considerations can help the assessment of creditworthiness by potentially sharpening the estimation of business risk, which is not directly observable in practice. Alternatively, from the standpoint of Altman (1968), ESG can enter as a new dimension to the existing information set of financial features used to gauge the likelihood of default.

2015. This is important as, Fitch, the third major ratings provider in the market, formally rolled out its ESG adoption around the end of 2017. To see whether ESG issues did in fact become salient in the ratings process, I begin by examining whether news on incidents related to ESG for companies matter for rating downgrades. That is, I first seek to test if ESG problems, from the potential risks they can carry, are playing a greater role as a positive contributor to credit ratings becoming downgraded during the period after Standard and Poor's (S&P) and Moody's declared their commitment to ESG but before Fitch announced its own ESG commitment.

As it turns out, news about problems related to ESG as a whole do not appear to contribute meaningfully to the determination of credit rating downgrades. While this may suggest that news about ESG problems are irrelevant to the credit rating agencies' assessment of risk, a closer look from decomposing ESG into its E, S, and G components reveal that incidents specifically related to the environment increase the likelihood of a ratings downgrade. A single environmental incident increases the probability of a ratings downgrade by around 27 percent. However, because environmental incidents tend to be infrequent (i.e. low mean and standard deviation), their actual economic significance to credit ratings is more modest. This increase, which is measured relative to that of Fitch, vanishes after Fitch releases its own ESG adoption initiative. No effects from environmental incidents are present outside the setting of ESG adoption. With respect to news about social and governance incidents, there is no impact to be found on rating downgrades from the initial (later) phase of ESG adoption by S&P and Moody's (Fitch).

Apart from rating downgrades, it is also interesting to consider whether the 'condition' of experiencing E/S/G incidents affects the level of credit ratings assigned to corporate bonds. From this perspective, I find no effect from news about either environmental or social incidents on the level of credit ratings. Incidents pertaining to corporate governance matter for credit ratings from S&P and Moody's historically more so than credit ratings from Fitch. Corporate governance incidents, however, did not become significantly more or less important in recent years with or without ESG adoption.

Given the orientation of credit ratings towards downside risk, news about environmental, social, or governance problems are natural candidates to consider in analyzing how credit ratings agencies have incorporated ESG-related concerns into their business. However, another source of ESG information is the ratings that are designed to assess overall corporate environmental, social, and governance performance. Here I am not making any assumptions about the accuracy of these ratings. Instead, I seek to understand the degree to which these E/S/G ratings, as widely used signals in the market, are reflected in credit ratings.

Based on the E/S/G ratings from the leading provider MSCI, which serves over 1,300 institutional investors, including 46 of the top 50 asset managers worldwide, I find that S&P and Moody's look more favorably upon credit assessments of bonds from firms with higher social ratings after the rating agencies' initial ESG adoption. In particular, a one standard deviation increase in social ratings corresponds to nearly a quarter of a letter grade increase in credit ratings. The positive effect from social ratings is not present for either environmental or governance ratings,[3] though S&P and Moody's appear to have placed a relatively stronger emphasis on governance ratings compared to Fitch in the past.

With the ongoing interest in carbon emissions from corporations due to their contribution to climate change, I consider, in addition to the above E/S/G-related signals, the carbon emissions score from MSCI. A higher carbon emissions score reflects a lower carbon footprint. While MSCI's ratings on environmental performance in general had some bearing on credit ratings, I find that its carbon emissions scores matter greatly for credit ratings. For credit ratings from S&P and Moody's after their ESG adoption, a one standard deviation increase in the carbon emissions score corresponds to more than a third of a letter grade increase their assigned credit ratings. The increase in the influence of carbon emissions relative to Fitch is more than halved in terms of magnitude after Fitch introduces its own ESG adoption.

Despite these significant alterations to credit ratings through the process of ESG adoption, it remains an open question as to whether the incorporation of ESG considerations actually improves the quality of these credit ratings. In particular, did ESG adoption enhance the ability of these ratings to predict future default? After all, this is the original motivation driving ESG adoption.

[3]To check the robustness of my results, I use Sustainalytics, a lesser known rater, as an alternative provider and discover qualitatively similar albeit weaker effects from social ratings and some positive effects from environmental ratings and no effect from governance ratings. These results are reported in the Appendix.

Although I find that better credit ratings indicate lower likelihood of future default, I do not discover consistent evidence suggesting that these ratings have become better in terms of predictive quality. Specifically, if I examine their ability to directly predict future default, no improvement in their predictive ability is to be seen.[4] By performing standard tests that examine the magnitude of the reaction from the stock market, either in terms of stock prices or trading volume, around rating downgrades, I observe no increase or decrease in terms of the informational value from these ratings from ESG adoption by S&P and Moody's relative to that of Fitch. As an additional test, I investigate the response from the fixed income market by studying the change in credit default swap (CDS) spreads around these rating downgrades and uncover some effects in the form of a widening of 10 to 20 basis points in CDS spreads in the downgrades by S&P and Moody's after their ESG adoption relative to those of Fitch. Given the stated motivations behind the promotion of ESG incorporation in credit ratings, these findings in their totality are quite surprising, though understandable given how issues with the quality of ESG data may diminish the potential informational value from incorporating ESG-related dimensions into the credit ratings analysis. Hence, the jury is, at best, still out regarding on how ESG adoption can fully deliver on its goal of improving the quality of credit ratings.

In relation to previous research, this paper contributes to the body of literature that studies the evolution of the credit ratings business and the problems that have arisen with this business over the years. Here, the impact of the rating agency behavior on the informational quality of their credit ratings is of great interest, but for different reasons than the ones that motivate this paper. For instance, in the aftermath of the financial crisis, a number of authors have pointed to the combination of credit rating agency competition and issuer shopping as a source of distortion in the quality of credit ratings (Bolton, Frexias, and Shapiro 2012; Becker and Milbourn 2011, Jiang, Stanford, and Xie 2012).[5] Because many institutional investors like pension funds and banks are barred (or, in some cases, strongly discouraged) by rules and regulations from investing in debt below a certain threshold (i.e. investment grade) as studied in Opp, Opp, and Harris (2013), my results point to ESG adoption as a new source from which distortions to the financial regulatory landscape can arise.

[4]The point estimates, in fact, suggest that credit ratings suffered in their predictive ability through ESG adoption.

[5]Research has shown that the quality of credit ratings can also be affected, on a limited basis, by transitioning credit analysts and select shareholders (Cornaggia, Cornaggia, and Xia 2016; Kedia, Rajgopal, and Zhou 2017).

The findings of this paper are also related to past studies that hint at a relationship between corporate social responsibility and firm risk. For example, in Hoepner, Oikonomou, Sautner, Starks, and Zhou (2018), firms that address their ESG problems on the advice of a large investor appear to reduce their downside risk. In a wider sample of firms, Amiraslani, Lins, Servaes, and Tamayo (2019) discover that firms with better corporate social responsibility enjoyed lower credit spreads and higher credit ratings during the two years of the financial crisis. Hong and Liskovich (2015) find that socially responsible firms in a small sample receive lower fines for foreign bribery. Ilhan, Sautner, and Vilkov (2019) document the effect of carbon emissions in options markets. While these results give reason to be optimistic, it is not clear if ESG is salient to firm risk on a more general basis. My findings suggest that the contribution of ESG issues to the area of credit risk can be large insofar as information about such issues are being mechanically introduced into credit ratings due to policy decisions by the credit rating agencies. In this respect, ESG-related information can appear to matter for credit risk through the credit rating agency channel regardless of whether ESG-related information itself contains any intrinsic relevance to credit risk.

The rest of the paper proceeds as follows. Section 2 introduces the data on credit ratings and the news archive about ESG issues as well as the E/S/G-related scores from MSCI. The sample selection, data processing and variable definitions are briefly explained. Section 3 discusses the recent move towards ESG by credit rating agencies in more detail. Section 4 presents the empirical analysis of this development for the credit ratings business. Section 5 offers concluding remarks.

2. Data and Summary Statistics

In this section, I describe the data sets used to study the effect of ESG adoption on the credit ratings business and present key summary statistics. I also explain how I put together the sample as well as the variables I use in the subsequent empirical analysis.

2.1. Corporate bond ratings

The data on corporate bonds (i.e. their ratings and the other characteristics) come from the Mergent Fixed Income Securities Database (FISD). For my purposes, I follow the prior literature, e.g. Badoer and Demiroglu (2019), in applying standard filters to construct my sample. I focus the analysis on U.S. corporate debentures, corporate medium-term notes, corporate medium-term zero coupon bonds, corporate strips, and corporate zero coupon bonds. I exclude bonds that are as a result of private placements as well as ones are issued by foreign entities (i.e. Yankee bonds) in the U.S. or are denominated in foreign currencies. Furthermore, I filter out bonds with any of the following characteristics: convertibles, asset-backed, mortgage-backed, perpetual, exchangeable, secured lease obligations, and credit enhancements.

2.2. News on issues related to ESG

The data on news about issues related to ESG is obtained from RepRisk, a Switzerland-based provider that grew out of the investment bank UBS in 2007. Its global coverage is extremely comprehensive as it tracks news mentions of ESG-related incidents involving approximately 11,000 publicly traded companies out of 79,000 companies in total. Incidents and their characteristics are identified by human analysts who remove duplicate mentions after an initial screening of news is performed via a proprietary algorithm. Within the ESG context, news incidents are tagged with particular issue(s) with a score of low, medium, or high for the severity of the incident. For news in the environmental category, I consider the following issues: 1) impact on landscape, ecosystems and biodiversity; 2) waste issues; 3) local pollution; 4) overuse and wasting of resources; 5) climate change, GHG emissions, and global pollution; 6) products (health and environmental issues). For news in the social category, I consider the following issues: 1) impact on communities; 2) human rights abuses and corporate complicity; 3) occupational health and safety issues; 4) poor employment conditions; 5) social discrimination; 6) forced labor; 7) child labor; 8) discrimination in employment; 9) animal mistreatment. For news in the governance category, I consider the following issues: 1) violation of national legislation; 2) tax evasion; 3) corruption, bribery, extortion and money laundering; 4) fraud; 5) executive compensation issues; 6) anti-competitive practices.

2.3. ESG Ratings

My information on the ratings that assess a company's overall performance in the areas of environmental, social, and governance come from MSCI, which is recognized by both academic and industry sources to be the largest ESG rating agency in this space (Eccles and Stroehle 2018; Fidelity 2021).

More than 1,200 institutional investors, including 46 of the top 50 asset managers worldwide, subscribe to these ESG ratings (MSCI 2017; Fidelity 2021). These facts are important in guiding my choice of ESG ratings given the proliferation of organizations, that offer ESG ratings, which are well known to differ considerably as discussed in Berg, Koelbel, and Rigobon (2020).[6] These MSCI ratings are the commercial ratings that range from 0 to 10 on a continuous scale, with 0 being the worst and 10 being the best. For more detailed information as well as the history behind these ratings, see Yang (2022). In my analysis, it is not essential that these ESG ratings are accurate descriptors of ESG performance but simply that they are the most widely used ESG signals in the market. In addition to these ESG metrics, MSCI also provides carbon emission scores, which follow the same scale.

2.4. Variables

The main variable of interest in this study are the credit ratings, which are converted from letters into integer codes from 22 being the highest and 1 being the lowest. Table 1 describes the mapping of these letter codes into their numerical counterparts, with Table 2 reporting their summary statistics. For each rating assignment, which is in the form of an upgrade, downgrade, affirmation, or confirmation, the number of high severity ESG-related incidents of the issuer are counted through the twelve months leading up to it. Information about daily stock returns and other financial characteristics of the firm is obtained from CRSP and Compustat. Hence, the number of observations here are conditional on matches with CRSP and Compustat. On average, more than a third of the credit rating assignments have a severe incident related to ESG preceding them. Incidents that are related to social, followed by governance, make up the majority of them. Firm characteristics, as found in Becker and Milbourn (2011), that are important control variables for analysis of credit rating assignments are also calculated. These are log sales, log assets, cash over total assets (and its square), EBITDA over total assets (and its square), cash flow over total assets (and its square), EBITDA over sales (and its square), cash flow over sales (and its square), property, plant, and equipment over total assets (and its square), interest expense over EBITDA (and its square), and debt over total assets (and its square).

Additionally, for the analysis of the market reactions to credit rating downgrades, I consider the

[6] Smaller raters exhibiting disagreement among themselves and with the mature incumbent rater need not imply that the ratings business as a whole is dysfunctional. For instance, in the search engine industry, Google is the most popular search engine tool and scores websites differently compared to Microsoft's Bing and Yahoo.

following bond-related characteristics: 1) bond size, which is the log of the maximum initial offering amount for downgraded bonds; 2) downgrade size, which is the absolute value of the maximum drop for all the downgraded bonds across all the rating agencies; 3) across investment grade, which equals one if any of the downgraded bonds crossed from investment grade into the speculative grade category according to any of the three rating agencies; 4) earnings announcement dummy, which equals to one if an earnings announcement occurs within either three days before or after the date of the rating downgrade. For this sample, I drop downgrades that were preceded by other downgrades within seven calendar days leading up to them. I am principally interested in rating downgrades as the consensus from past research, as discussed in Badoer and Demiroglu (2019), is that rating upgrades generate no significant effect on prices. In the case where multiple bonds for a given firm are downgraded on the same day, it is treated as one event. I also drop cases where the downgrades by Fitch coincided with downgrades by Moody's or S&P. For my analysis involving credit default swaps, I obtain data on daily CDS spreads from the Markit Group and use the 5-year CDS contract given that it is most actively traded (Kedia, Rajgopal, and Zhou 2017).

3. ESG Adoption by Credit Rating Agencies

Before I delve into the empirical analysis, I start by first discussing the historical background that lies behind credit rating agencies and the integration of ESG into their practice. To provide some concrete illustrations of what has been labeled as ESG integration, I discuss a few anecdotes in which ESG was reportedly a contributor to ratings becoming downgraded.

3.1. Historical Background

From the time of their initial founding around the beginning of the twentieth century, credit rating agencies have operated with a very specific objective: providing signals to the market about the likelihood that creditors will get paid back on debt securities that they own. In a 2002 statement to the U.S. Securities and Exchange Commission, S&P touts credit ratings as an 'effective and objective tool for the market to evaluate and assess credit risk' (SEC 2002). To perform their credit analysis, credit rating agencies rely on 'publicly available financial reports and financial statements' as well as potentially non-public 'budgets and forecasts, financial statements on a stand-alone basis, internal capital allocation schedules, contingent risks analyses and information relating to new financings, acquisitions, dispositions and restructurings' (SEC 2002). The latter is permissible under an exemption to Regulation FD carved out for credit rating agencies (Jorion, Liu and Shi 2005). At no point here did S&P publicly mention or allude to environmental and social problems of the firm.

Since then, attitudes have changed. A press release by Moody's Investor Services in September 2015 formally outlined its approach to credit ratings that factors ESG considerations into its analysis of credit risk (Moody's 2015). Within a few weeks, S&P (2015) put forth a similar public statement about its position on ESG adoption with a special emphasis on the environmental aspect of ESG and noted that it expected environmental information to play a bigger role in its ratings in coming years. The rationale behind their emphasis on ESG is that incorporating ESG issues into their information set will enhance their understanding of credit risk (Moody's 2015; S&P 2015). These statements by the major credit rating agencies are noteworthy because it is not as though firms did not have environmental and social problems in the past. Concerns about these problems have long been the subject of much discussion in public policy circles, which typically treat them as environmental and social externalities. If these statements are taken at face value, then credit rating agencies can potentially serve as a channel through which the market becomes more informed about credit risk while simultaneously internalizing externalities that are normally the responsibility of the government. To be clear, these statements are not so much about promulgating a fundamental change to the internal rules that govern the determination of credit ratings but more about publicly signaling their interest in incorporating ESG-related issues into their analysis.[7] This is akin to the practice of U.S. government agencies issuing guidance or other formal public statements about how existing laws are applied (e.g. a government statement that directs focus towards the problem of illegal drug trafficking even though the punishment for illegal drug trafficking is unchanged). Citing widespread public interest in ESG, Fitch subsequently produced its ESG adoption initiative near the end of 2017 (Fitch 2017).

[7]Prior to the announcements of these formal ESG adoption initiatives, these credit rating agencies conducted small-scale 'pilot' programs that looked into ESG factors in their ratings process. The number of rating actions affected by these programs was de minimis, i.e. extremely small. For instance, S&P (2015) notes that ESG considerations contributed to only 19 downgrades in this pre-announcement period. There were also around 200 cases in which S&P (2015) considered environmental and climate information in their credit analysis but were not used in the formation of a rating action. In my analysis, I check that the important effects from social ratings and carbon emissions documented do not exhibit significant trends prior to ESG adoption by Moody's and S&P at the end of 2015 (see Figure 1).

3.2. Examples

As much as credit rating agencies have outlined in broad strokes their approach to integrating ESG factors into their ratings processes, there is still much opaqueness in terms of how such ESG adoption policies have been carried out in practice. To shed more light on the phenomenon, I consider a few case studies from S&P (2017) that have been exemplified as instances where ESG factors reportedly contributed to rating downgrades.

Case study 1: ExGen Texas Power

Date of ratings downgrade: January 13, 2016

Action: Downgraded from BB- to B+

Key rationale: Power prices in the Electric Reliability Council of Texas (ERCOT) had depressed during the previous year and were expected to remain depressed.

Discussion by the rating agency: *We downgraded ExGen Texas Power based in the U.S. The downgrade was due to ongoing low power prices in ERCOT, which reflect lower natural gas prices, sluggish growth in demand (based on a weaker oil and gas sector in Texas), and greater-than-expected renewable generation that has cut into peak demand and weakened market heat rates. Consecutive downgrades continued for ExGen with the most recent on March 16, 2017, when we lowered the rating to 'CCC-' in light of diminished market conditions. Here we view competition from greater-than-expected renewable generation as compatible with the TCFD's definition of technology risk.*

Case study 2: Agrofresh

Date of ratings downgrade: June 10, 2016

Action: Downgraded from B+ to B

Key rationale: Weaker-than-expected operating performance from exposure to adverse weather impacts on the apple crop.

Discussion by the rating agency: *We downgraded AgroFresh, a U.S.-based company that uses SmartFresh–a technology that preserves fruits. Adverse weather conditions had been a primary driver of the weaker performance due to effects on the global apple crop, which drives an overwhelming majority of the company's revenues and EBITDA. My assessment of a weak business risk profile took into account the risks related to AgroFresh's narrow focus, key patent expirations, and potential changes* *in consumer preferences. Although weather impacts on crop yield, competition, and patent expirations were the key to the rating change, we viewed the trend toward organic produce as a potential risk factor that could affect demand for fruits preserved with treatments like SmartFresh over the intermediate term. We view this as a transition risk as defined by the TCFD.*

In both of these cases, there exist obvious financial reasons that caused the rating agency to decide to downgrade these credit ratings. Poor business performance and adverse market conditions are standard considerations that factor into these assessments. At the same time, however, some of these problems can potentially be tied to environmental and social drivers (e.g. the desire to embrace cleaner forms of energy and preferences for more socially responsible methods of agriculture).[8] While these anecdotes are illustrative, they are also ambiguous from visual inspection. An independent and comprehensive quantitative analysis is warranted to fully understand how issues about ESG may (or may not) be contributing to these credit rating downgrades.

4. Empirical Analysis

In this section, I study the effect of ESG adoption on the credit ratings business. I first examine the degree to which news about ESG problems and other ESG-related signals affect credit rating assignments. I then proceed to investigate if ESG adoption has had any impact on the informational quality of these ratings.

4.1. Predicting Credit Ratings Downgrades with ESG Incidents

If concerns pertaining to ESG reportedly factor into the credit ratings process, then how much do news incidents related to ESG matter when credit ratings are downgraded? To explore this question, I start by estimating the following regression:

$$Downgrade_{j,k,t} = \zeta ESG\ Incidents_{j,t} + Year\ FE + Bond\ FE + \eta_{j,k,t}, \tag{1}$$

[8]While these credit rating agencies made their general commitment towards adopting ESG known to the investing public, there is a great deal of opacity surrounding their actual implementation as the discussion of ESG issues is generally not found in the original explanations of credit rating assessments. For example, there was no reference to organic agriculture or TCFD in its original discussion of the June 10, 2016 downgrade of Agrofresh.

where $ESG\ Incidents_{j,t}$ measure the number of severe news ESG-related incidents in the twelve months leading up to the rating assignment (i.e. downgrade, upgrade, affirmation or confirmation) for bond j at calendar date t. $Downgrade_{j,k,t}$ takes on a value of 1 if the bond is assigned a lower rating by credit rating agency k and zero otherwise. The time period here is 2012-2019.

Table 3, in its Column 1, reports the estimation results, which indicate that the number of severe ESG incidents in the news on average do not predict credit rating downgrades at all. This observation is unchanged with the inclusion of firm characteristics (calculated from the most recent annual accounting data leading up to the rating downgrade): log sales, log assets, cash over total assets (and its square), EBITDA over total assets (and its square), cash flow over total assets (and its square), EBITDA over sales (and its square), cash flow over sales (and its square), property, plant, and equipment over total assets (and its square), interest expense over EBITDA (and its square), and debt over total assets (and its square).

Given the recent move to adopt ESG by Moody's and S&P and the high number of observations in this sample, I can investigate the above baseline predictive regression further by using the following specification:

$$
\begin{aligned}
(2) \quad Downgrade_{j,k,t} = {} & \phi_1 ESG\ Incidents_{j,t} + \phi_2 Treatment_k + \phi_3 ESG\ Incidents_{j,t} \times Treatment_k \\
& + \phi_4 ESG\ Incidents_{j,t} \times Post1_t + \phi_5 ESG\ Incidents_{j,t} \times Post2_t \\
& + \phi_6 Treatment_k \times Post1_t + \phi_7 Treatment_k \times Post2_t \\
& + \phi_8 ESG\ Incidents_{j,t} \times Treatment_k \times Post1_t \\
& + \phi_9 ESG\ Incidents_{j,t} \times Treatment_k \times Post2_t + Year\ FE + Bond\ FE + \eta_{j,k,t},
\end{aligned}
$$

where I break up the post-period after the initial ESG adoption by Moody's and S&P into two phases: $Post1$ is equal to 1 for the years 2016-2017 (i.e. after Moody's/S&P ESG adoption but before Fitch's) and 0 otherwise and $Post2$ is equal to 1 for the years 2018-2019 (i.e. after Fitch's ESG adoption) and 0 otherwise. $Treatment_k$ is equal to 1 if the downgrade action is from S&P or Moody's and 0 if from Fitch. The main coefficient of interest is ϕ_8, which estimates the effect of $ESG\ Incidents_{j,t}$ on credit rating downgrades after the initial ESG adoption by Moody's and S&P relative to Fitch.

Columns 3 and 4 in Table 3 report the estimation results for Equation 2. Regardless of whether I include the host of firm characteristics as controls, ESG incidents, as a whole, offer essentially nothing in terms of either economic or statistical significance for predicting credit rating downgrades.

Now could the effects be different if I looked at the environmental, social, and governance aspects separately? It is possible that one category is assigned more importance than the other and ESG in the aggregate obfuscates the effects from the individual E/S/G components.

Table 4 examines the predictive ability of environmental, social and governance incidents. In Columns 1 and 2 of Table 4, I observe that the role of environmental incidents in the determination of credit rating downgrades takes on a much greater importance following ESG adoption by S&P and Moody's.[9] A single environmental incident increases the chance of a credit rating downgrade by a little more than 25 percent. While this may suggest that environmental incidents play a large role in the assessment of credit ratings, it should be noted that such incidents are relatively uncommon. A one standard deviation increase in environmental incidents corresponds to only around a six percent increase in the likelihood of a downgrade in credit ratings. Apart from this ESG adoption initiative, there is no indication that environmental incidents were meaningful contributors to credit rating downgrades on a general basis or over time in this entire period. After Fitch produced its ESG adoption initiative, the relative difference with respect to the influence of environmental incidents between S&P and Moody's versus Fitch disappears.

To systemically explore the implications of ESG adoption, I examine social and governance incidents as potential drivers of downgrades. In contrast to the environmental dimension, social and governance incidents in Columns 3 through 6 of Table 4 do not appear to matter much for credit ratings. This is true regardless of whether I am looking at the overall effects[10] or at the relative effects by group (i.e. S&P and Moody's versus Fitch) and time period.

[9] In the Appendix, for the sake of completeness, I report my analysis of credit rating upgrades and detect no strong effects.

[10] In an unreported set of results, I also consider Equation 1 for these E, S, and G incidents and discover similarly weak coefficients for them.

4.2. Credit Ratings and ESG-related Signals

With the above analysis on news about E/S/G incidents and the likelihood of credit rating downgrades, it is interesting to consider whether the 'condition' of experiencing such E/S/G problems impacts the credit ratings assigned. Presumably, if these E/S/G problems are viewed by credit rating agencies as indicative of future risks (e.g. divestment from investors, increased regulatory pressure), then a focus by credit rating agencies via ESG adoption towards these problems may result in lower credit ratings for bonds associated with firms linked to these problems. In a set of similar specifications to Equation 2 but for the level of credit ratings instead of an indicator variable for their downgrades, Columns 1 through 4 in Table A.2 of the Appendix show that environmental and social incidents have little to no bearing on the level of credit ratings.[11] On the other hand, governance incidents of the firm in Columns 5 and 6 of Table A.2 have, in the past, adversely affected the bond ratings assigned by Moody's or S&P.[12] For a single governance incident, the credit rating is negatively affected by about half a notch. Despite ESG adoption process by Moody's and S&P (or later by Fitch), no significant changes in the role of governance incidents in the determination of credit rating assignments are found.

While E/S/G incidents of the firm, in some cases, may matter for the determination of credit ratings, such information represents only one part of the set of commonly observed signals about ESG in the market. For all the potential pitfalls and flaws associated with the ratings that are supposed to measure overall ESG performance, ESG ratings have been extremely influential and offer a different perspective on the behavior of the firm with respect to ESG. In particular, for the ratings from MSCI, which is the largest ESG rating agency, its clients number over 1,300 institutional investors, which include 46 of the top 50 asset managers worldwide. Unlike E/S/G incidents, these E/S/G ratings also take into account of a company's current practices and policies towards addressing problems related to environmental, social and governance.

Table 5 reports the results from the analysis in which I assess the degree to which credit rating assessments are driven by environmental ratings, which ought to have a positive coefficient if Moody's and S&P are placing more emphasis on them through their ESG adoption. Column 1 of Table 5

[11] This is in line with the fact that one standard deviation change in environmental incidents having a weak effect in terms of magnitude on the chance of a ratings downgrade.

[12] While ESG is the focus on my study, I observe some evidence of Fitch being more lenient with its ratings than Moody's and S&P in some of my analyses as first noted in Cantor and Packer (1995).

indicates some evidence in support of this hypothesis as a one standard deviation increase in environmental ratings correspond to more than a quarter of a letter grade increase for credit ratings (relative to Fitch) after ESG adoption by Moody's and S&P. With the inclusion of standard financial characteristics listed earlier, this effect, in Column 2 of Table 5, remains positive though slightly weaker and statistically insignificant. In both Columns 1 and 2 of Table 5, it is in the period after Fitch also adopts ESG where we see this effect (relative to Fitch) is greatly diminished.

In the case of social ratings, they play a comparatively larger role in the determination of credit ratings as indicated in Columns 3 and 4 of Table 5. With ESG adoption by Moody's and S&P, their credit ratings positively reflect social ratings. A one standard deviation increase in social ratings corresponds to nearly a quarter of a letter grade increase in credit rating. Adding firm controls in Column 4 of Table 5 barely affects this point estimate. After all three raters have introduced ESG integration into their practices, this increase, in terms relative to Fitch, is whittled away.

Similar to news pertaining to governance incidents, these ratings about governance contributed no more than they did to credit ratings before ESG adoption by the credit rating agencies. This is not to say that they are completely irrelevant. Columns 5 and 6 of Table 5 report a historically positive impact from governance ratings on the credit ratings assigned by S&P and Moody's. The positive effect is related to Ashbaugh-Skaife, Collins, and LaFond (2006) who document the benefits of stronger corporate governance for these credit ratings. The size of this effect from governance is somewhat weak in magnitude as a one standard deviation increase in governance ratings corresponds to one-sixth of a letter grade increase on average in the credit rating assigned.

While the ratings from the leader MSCI are important, I also consider whether the documented effects substantially vary when I examine Sustainalytics as a source for an alternative set of E/S/G ratings.[13] I find that similar, albeit somewhat weak, positive effects, through ESG adoption by Moody's and S&P, on credit ratings from environmental and social ratings, which average around 63 and 60 with a standard deviation 14 and 9.5 on 0-to-100 point scale, respectively. For governance ratings, the

[13]According to the Wall Street Journal, another notable ESG rater is Thomson Reuters, which is also known as Refinitiv/Asset4 (Shifflett 2021). I do not consider these ratings in my analysis as it has been shown in the Berg, Fabisik, and Sautner (2020) that the ratings data from Thomson Reuters contain look-ahead bias due to its practice of re-writing their ratings with future information.

effects are generally quite small. I report these results in the Appendix.

Among the various concerns pertaining to environmental, social, and governance is the related issue of climate change and the carbon emissions from corporations that drive it (Bolton and Kacperczyk 2021). As concerns in this particular area have translated into risks for the businesses involved, credit rating agencies have, within their ESG adoption framework, expressed interest in these problems. Looking at the carbon emissions score from MSCI, I observe higher carbon emission scores are reflected in better credit ratings for Moody's and S&P after their ESG adoption in Table 6. A higher carbon emission score indicate a lower carbon footprint. In terms of magnitudes, a one standard deviation increase in carbon emissions score corresponds, in Column 3 of Table 6, to almost a half letter grade increase in credit rating, so the effect is nearly twice as strong compared to that from social ratings.[14] Again, with the introduction of firm controls in Column 4 of Table 6, the estimates are similar though slightly weaker. Outside of this setting of ESG adoption, carbon emissions do not appear to generally factor strongly into credit ratings historically, either before or after the time of ESG adoption. This is important because one might imagine that credit ratings may have already reflected carbon emissions in the past or that carbon emissions became more important for credit ratings over time through economy-wide shocks.[15] Once Fitch performs its own ESG adoption, the relative differences in how much carbon emissions are reflected in ratings, as expected, weakens, i.e. is more than halved.

From the range of ESG-related signals investigated in this paper, social ratings and carbon emissions emerge as the strongest factors influencing credit ratings in the context of ESG adoption by Moody's and S&P.[16] However, given that the discussion of these factors in financial markets precedes ESG adoption, one may be concerned the positive effects from social ratings and the carbon emissions

[14]While my analysis focuses on the overall impact, I observe that, in unreported regressions, the positive effect on credit ratings from a better carbon emissions score is restricted to bond credit ratings within investment grade. For bonds whose ratings are in the speculative grade category, a better carbon emissions score has a negative effect on the ratings assigned. This suggests that, when businesses are under distress, being carbon-friendly is viewed negatively by S&P and Moody's under their ESG adoption initiative. For social ratings, its positive effect is more or less homogeneous between investment grade and speculative grade bonds.

[15]For instance, Seltzer, Starks, and Zhu (2021) show how credit ratings suffered for firms with higher carbon emissions after the international Paris Climate Agreement. For further robustness, in unreported tests, I check that the effects I identify here are virtually identical if I restrict my sample to bonds rated by Fitch as well as either Moody's or S&P.

[16]In the Appendix, I check that these effects are not strongly present for credit rating downgrades or upgrades. Similar to the level of credit ratings, social ratings and carbon emissions tend to be quite persistent across time for each firm.

score were already starting to appear in a significant trend for Moody's and S&P prior to their ESG adoption at the end of 2015. To address this concern, I begin by considering the following dynamic specification for social ratings for the years immediately leading up to ESG adoption by Moody's and S&P:

$$
\begin{aligned}
(3) \qquad Credit\ Rating_{j,k,t} = \sum_{2013 \leqslant t \leqslant 2015} \psi_t Social\ Rating_{j,t} \times Treatment_k \times 1_t \\
+\psi_1 Social\ Rating_{j,t} \times Treatment_k \times Post1_t + \psi_2 Social\ Rating_{j,t} \times Treatment_k \times Post2_t + \\
other\ terms + Year\ FE + Bond\ FE + \eta_{j,k,t},
\end{aligned}
$$

where *other terms* refer to the main effects and pairwise interactions as well as firm controls used previously that are included, but not displayed for brevity, in Equation 3. The dummy variable 1_t (omitting 2012) is equal to 1 if the credit rating is assigned in year t and 0 otherwise. The definitions of the other variables here are the same as found above.

Figure 1, Panel A plots the estimates from Equation 3. Credit ratings from Moody's and S&P were clearly not being increasingly affected by social ratings in any significant way in the time running up to their ESG adoption, which resulted in an uptick in the effect from social ratings before vanishing with Fitch's commitment to ESG. In Panel B of Figure 1, similar results are displayed for the same specification when it is applied to the carbon emissions score.

4.3. Informational Quality of Credit Ratings

With this paradigm shift in the credit ratings business, a key question is whether the practice of ESG integration has altered the informativeness of these ratings. The question is important because ESG integration for credit rating agencies is solely directed at enhancing their understanding of the creditworthiness of borrowers and consequently the ability of their ratings to inform investors about future default. To this end, I first look at the predictive quality of credit ratings vis-à-vis future default. To assess the extent to which the overall informativeness of credit ratings are affected by ESG adoption, I examine the average short-term stock price reactions as well as trading volume to rating downgrades. The intuition behind the latter analysis is that credit rating downgrades should trigger stronger reactions in the stock market for when such changes convey more valuable incremental information to the market. As a further test of market responses, I consider credit default swaps whose spreads should increase from more informative rating downgrades.

4.3.1 Future Default

In this part of the analysis that studies the informational quality of credit ratings in the context of ESG adoption, I consider the ability of these bond ratings to predict future default. Default is defined as receiving a credit rating of 'C', which indicates that default of the obligation is regarded as beyond a virtual certainty, or a 'D,' which indicates that the obligation is in default. For my main analysis, I look at the occurrence of default within the next 24 months of the rating assignment. Due to limitations associated with the relatively recent nature of ESG adoption as well as the desire of obtaining a 'clean' estimate of the impact of ESG adoption by S&P and Moody's, I focus on the time period 2012-2017.[17]

Using this narrower sample, I estimate the following regression:

$$
\begin{aligned}
(4) \qquad Default_{j,k,t} = {} & \rho_1 Credit\ Rating_{j,k,t} + \rho_2 Treatment_k + \rho_3 Credit\ Rating_{j,k,t} \times Treatment_k \\
& + \rho_4 Credit\ Rating_{j,k,t} \times Post_t + \rho_5 Treatment_k \times Post_t \\
& + \rho_6 Credit\ Rating_{j,t} \times Treatment_k \times Post_t + Year\ FE + Industry\ FE + \epsilon_{j,k,t},
\end{aligned}
$$

where $Default_{j,k,t}$ is equal to 1 if bond j experiences default, according to any credit rating agency, at any point over the next 24 months given its rating assignment at time t and 0 otherwise. $Post_t$ is equal to 1 if the rating assignment took place in the years 2016-2017 and 0 otherwise. $Treatment_k$ is defined the same as above.

Table 7 reports the estimation results from predicting future default in Equation 4.[18] As one would expect, Columns 1 through 3 of Table 7 reveal that bonds assigned with higher credit ratings have

[17] It is less clear what the effects, measured in relative terms, in the subsequent years ought to look like once Fitch joins S&P and Moody's in ESG adoption. The coefficient would here depend on the effectiveness of ESG integration by S&P and Moody's as well as that of Fitch.

[18] In these regressions and earlier ones that predict the likelihood of being downgraded, I use the linear probability model, which produces coefficients that are more intuitively interpretable as seen in recent top publications on credit ratings (Becker and Milbourn 2011; Badoer and Demiroglu 2019). In a setting where events like downgrades or default are infrequent, it is shown in King and Zeng (2001) that the linear probability model produces unbiased estimates whereas logit does not. Recent work by Timoneda (2021) from political science shows the linear probability model produces more accurate estimates than logit when the binary dependent variable is equal to 1 less than 25% of the time.

a lower chance of experiencing default over the next 24 months. The incremental predictive effect in Column 4 remains qualitatively consistent and similar in magnitude upon controlling for the host of financial characteristics used in the previous tables. While ratings by S&P and Moody's in Columns 5 and 6 tend to be better at predicting default compared to those from Fitch, I detect no benefit to predictive ability through ESG adoption. While the standard errors are somewhat large, the sign and magnitudes of the estimates of ρ_6 are telling in their own right. Contrary to the aims of ESG adoption, the sign and magnitudes of the estimates of ρ_6 in these two columns indicate that predictive quality markedly worsened. In the Appendix, I report similar results if I examine defaults over the next 12 months as an alternative horizon.[19]

4.3.2 The Impact of Rating Downgrades

Although examining the ability of ratings to predict future defaults provides an immediate test for changes in their informational quality, one caveat is that I am restricted to examining defaults occurring over the horizons of a few years as, for instance, analyzed in Badoer and Demiroglu (2019). As a result, such tests can neglect potential benefits to the informational content of credit ratings through ESG adoption with regards to default in the distant future. To address this drawback, I take a standard approach found in the empirical literature that measures the informativeness of credit ratings via short-term stock price reactions to rating downgrades (Badoer and Demiroglu 2019; Chava, Ganduri, and Ornthanalai 2019; Jorion, Liu, and Shi 2005). For credit ratings to provide more useful incremental information to investors, their downgrades should generate a stronger reaction in stock prices.[20] The phased ESG adoption process (i.e. Moody's and S&P first at the end of 2015, then Fitch at the end of 2017) is again helpful here in that it gives us the opportunity to estimate the impact on informativeness by comparing the reactions to downgrades from Moody's and S&P against those of Fitch before and after 2015. Specifically, I estimate the following difference-in-differences specification:

$$Price\,Impact_{i,t} = \delta_1 Treatment_i \times Post_t + \delta_2 Treatment_i + Year\ FE + \xi_{i,t}, \tag{5}$$

[19]For credit ratings within the investment grade category, there were almost no occurrences of default in either 1-year or 2-year horizon. For credit ratings that were CCC or lower, I observe default rate (in percentage) in the double digits, i.e. 32 percent for the 1-year horizon and 37 percent for the 2-year horizon. The magnitudes reported here are on par with default rates disclosed annually by the major rating agencies like S&P (2021).

[20]I focus on rating downgrades as previous studies like Ederington, Yawitz, and Roberts (1987) and Badoer and Demiroglu (2019) have consistently found that rating upgrades produced no significant price effects.

where $Treatment_i$ is a dummy variable equal to 1 if the rating downgrade came from S&P or Moody's and 0 otherwise. $Post_t$ is a dummy variable equal to 1 if the rating downgrade took place in 2016 or afterwards.

There are several advantages to this specification. First, it allows us to deal with the worry that the market might give more weight to rating actions by Moody's and S&P as they are slightly bigger names than Fitch in the credit ratings business. Second, by including year fixed effects, I account for the fact that the role of credit ratings and the overall reputation of their providers in the credit ratings business may vary over the years. In addition to these terms, I also include several variables that could potentially matter for the dependent variable. Because I might be concerned that incorporating ESG issues fuels larger downgrades, I control for downgrade size as defined in the previous section. Related to this point, I also control for whether the rating was dropped from investment grade to speculative grade given how certain institutions face regulatory pressure to hold investment grade securities. If larger borrowers have more ESG problems and downgrades of larger debt issuances matter more to investors, then bond size can be salient too. These features of bond downgrades (as well as a dummy for whether an earnings announcement occurred within three days before or after a downgrade) plus standard firm characteristics like leverage (i.e. debt divided by total assets), operating performance (i.e. operating income over total assets), cash (scaled by total assets), and size (i.e. log total assets) are added as controls.

To calculate the price impact of rating downgrades, I start by computing the cumulative abnormal returns (CARs) around the time of the downgrade event. I estimate abnormal returns (ARs) for firm i on time t as

$$AR_{i,t} = R_{i,t} - E(R_{i,t}), \tag{6}$$

where expected returns are based on coefficients calculated in

$$R_{i,t} = \alpha_i + \beta_{i,1}MKT_t + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}MOM_t + \epsilon_{i,t} \tag{7}$$

over a [-30,-250] day estimation window leading to the rating downgrade event. A minimum of 100 days is required for the estimation. MKT_t, SMB_t, HML_t, and MOM_t are the returns from the market, size, and value factors in Fama and French (1993) and the momentum factor in Carhart (1997), respectively. The CAR for the n-day announcement window is then the sum of the ARs starting $\frac{n-1}{2}$ day(s) before and ending $\frac{n-1}{2}$ day(s) after that ratings downgrade announcement date. The time period of interest is 2012 through 2017. I arrive at my final measure of price impact by taking the absolute value of the CAR. This is to err on the side of caution because not all credit downgrades are bad news for stockholders.[21] While a credit rating downgrade on average creates a negative stock price response,[22] a downgrade can also convey good news to stockholders if the motivation behind the downgrade is driven by concerns regarding a transfer of wealth from bondholders to stockholders via an increase in leverage instead of concerns about financial performance as first pointed out by Goh and Ederington (1993). For instance, the fast food company McDonald's experienced a roughly two percent gain in its cumulative abnormal stock return over the [-2,+2] window after Moody's downgraded its bond rating by one notch from A2 to A3 on May 15, 2015 for pursuing more aggressive financial policies involving increases in debt that were stated to favor shareholders.[23]

Table 8, Panel A reports the estimation results of Equation 5. In Columns 1 and 2, which report the effects calculated with respect to the returns over the [-1,+1] window around rating downgrades, I discover no increase or decrease in the price impact of downgrades by Moody's and S&P versus Fitch after ESG adoption by Moody's and S&P at the end of 2015. This observation continues to hold when I consider alternative windows like [-2,+2] and [-3,+3] for the short-term price impact in Columns 3 through 6. From these findings, it would appear that credit ratings became no more informative than before despite the changes made to them through ESG adoption.

For robustness, I consider abnormal trading volume as an alternative, and arguably more sensitive, indicator of the market's reaction to credit rating downgrades. As first pointed out in Beaver (1968), trading volume captures changes in individual belief revisions that could potentially be averaged out in pricing data. In this respect, trading volume may detect impacts that may otherwise go unnoticed

[21]In an unreported set of regressions with CAR as the dependent variable, I find some evidence of a more negative price reaction on average from rating downgrades by Moody's and S&P after their ESG adoption compared to those by Fitch.

[22]In my sample, the mean CAR for rating downgrades over the [-2,+2] window is approximately -1 percent.

[23]See https://www.moodys.com/research/Moodys-downgrades-McDonalds-unsecured-ratings-to-A3-and-commercial-paper–PR_325519, last visited June 20, 2021.

if I only examine stock returns.[24] Whereas stock returns reflect changes in expectations from the market as a whole, trading volume reflect changes in expectations of individual market participants (Bamber, Barron, and Stevens 2011).

To calculate abnormal trading volume (AV) for firm i on time t, I take a similar approach to stock returns:

$$AV_{i,t} = V_{i,t} - E(V_{i,t}), \tag{8}$$

where expected trading volume is based on coefficients calculated in

$$V_{i,t} = \gamma_0 + \gamma_1 VMKT_t + \epsilon_{i,t} \tag{9}$$

over a [-30,-250] day estimation window leading to the rating downgrade event, with the requirement that there be no less than 100 trading days for the estimation. $V_{i,t}$ is the daily trading volume scaled by the number of shares outstanding for firm i at time t. $VMKT_t$ is the daily trading volume, also scaled by the total number of shares outstanding, for the market composed of all firms in the CRSP universe at time t. The cumulative abnormal trading volume (CAV) for the n-day announcement window is then the sum of the AVs starting $\frac{n-1}{2}$ day(s) before and ending $\frac{n-1}{2}$ day(s) after that ratings downgrade announcement date. The average CAV over the [-2,+2] window is 0.028.

The trading volume analysis is reported in Panel B of Table 8. Across the various time windows, i.e. [-1,+1], [-2,+2], [-3,+3], I observe no relative differences between Moody's and S&P versus Fitch in terms of abnormal trading volume around credit rating downgrades. My results here are consistent with the lack of change in informational value in credit ratings despite the adoption of ESG by Moody's and S&P.

Although the stock market is a standard setting for tests of informativeness of credit rating downgrades, one additional place to look at is the fixed income market, which has a direct link to credit ratings. While bond prices are, in principle, affected by credit rating downgrades, the well-known

[24] In Flannery, Hirtle, and Kovner (2017), this measure is used to evaluate the informational value of bank stress tests by the Federal Reserve.

infrequency of bond trading in practice makes it challenging to establish reliable inferences about changes in bond prices around short time windows surrounding such downgrades. As a result, I examine credit default swap (CDS) spreads, which serve as a barometer, at the daily frequency, for credit risk. Following Kedia, Rajgopal, and Zhou (2017), I use the 5-year CDS contract owing to the fact that it is the most actively traded contract. If a rating downgrade becomes more informative, then the increase in CDS spread should become larger.

Applying the same specification as seen in the above analysis involving the stock market but now to the change in CDS spreads (in basis points), I include the lagged change in CDS spread as an additional control to account for potential market anticipation of rating downgrades. For the change in CDS spreads in the [-1,+1]/[-2,+2]/[-3,+3] window, the lagged change in CDS spreads is defined over the [-10,-2]/[-11,-3]/[-12,-4] window. Table 9 reports the results, which indicate, across the various short-term windows, an increase of around 15 basis points in the CDS spreads for rating downgrades by S&P and Moody's after their initial ESG adoption (relative to Fitch). On average, the CDS spread in my sample is about 133 basis points. Due to the limited size of my sample, the statistical significance is borderline. Nevertheless, these findings from the CDS market are encouraging given the stated purpose of incorporating ESG in order to improve credit ratings quality and the total absence of changes in informational quality of credit ratings in the other empirical tests found in the literature.

5. Conclusion

The stated recognition of ESG issues by credit rating agencies marks an exciting moment in the historical timeline of the credit rating business, which traditionally have assigned little weight to these concerns. With ESG adoption by the key players in this business, I document significant changes to the determination of credit ratings: 1) firms that score well in terms of a lower carbon footprint tend to enjoy higher credit ratings for their corporate debt; 2) firms that have higher social ratings also benefit in their bond rating assessments. Corporate governance, while historically important, play no greater role than before in the determination of credit ratings. One overall implication of these results is that ESG adoption by credit rating agencies can act as a mechanical means through which ESG-related information becomes important for credit risk irrespective of the intrinsic value of ESG-related information to credit risk.

To investigate what these changes mean for the informational quality of credit ratings, I examine the ability of credit ratings to predict future default. Although better credit ratings correspond to a lower rate of future default, I observe no improvement in their predictive ability from ESG adoption. An analysis of the market impact from credit rating downgrades reveal mixed evidence of changes to the informational quality of credit ratings. From these standard approaches to testing rating quality in the literature, the lack of conclusive evidence towards the improvement of ratings quality is concerning given that the goal of ESG adoption is to enhance their assessment of credit risk. This is analogous to showing that standard tests of drug efficacy reveal no convincing evidence of improvement in patients' health for a new drug being promoted in the market.

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Table 1

Numerical Classification of Credit Ratings

	Credit rating agencies			
Type	Moody's	S&P	Fitch	Numerical Scale
Investment Grade	Aaa	AAA	AAA	22
	Aa1	AA+	AA+	21
	Aa2	AA	AA	20
	Aa3	AA-	AA-	19
	A1	A+	A+	18
	A2	A	A	17
	A3	A-	A-	16
	Baa1	BBB+	BBB+	15
	Baa2	BBB	BBB	14
	Baa3	BBB-	BBB-	13
Speculative Grade	Ba1	BB+	BB+	12
	Ba2	BB	BB	11
	Ba3	BB-	BB-	10
	B1	B+	B+	9
	B2	B	B	8
	B3	B-	B-	7
	Caa1	CCC+	CCC+	6
	Caa2	CCC	CCC	5
	Caa3	CCC-	CCC-	4
	Ca	CC	CC	3
	C	C	C	2
		D	D/DD/DDD	1

Notes. This table presents the ratings assigned by the three credit rating agencies: Moody's, Standard and Poor's (S&P), and Fitch. Moody's does not assign a rating for default. The right hand side displays the how each set of ratings converts into a numerical code.

Table 2

Main Descriptive Statistics

	N	Mean	Standard Deviation	Median
Credit Rating	40,231	15.159	2.578	15
Bond Default	34,523	0.004	0.066	0
ESG Incidents in the News	40,231	0.386	1.289	0
Environmental Incidents in the News	40,231	0.056	0.279	0
Social Incidents in the News	40,231	0.193	0.698	0
Governance Incidents in the News	40,231	0.137	0.452	0
Environmental Rating	37,280	6.145	2.394	6.200
Social Rating	37,280	4.308	1.837	4.140
Governance Rating	37,280	4.994	2.461	4.700
Carbon Emissions Score	36,274	8.286	2.437	9.800
Log Sales	40,231	10.100	1.184	10.141
Log Assets	40,231	11.109	1.579	10.855
Cash/Assets	40,231	0.128	0.117	0.088
EBITDA/Assets	40,231	0.108	0.113	0.114
Cash flow/Assets	40,231	0.086	0.063	0.086
EBITDA/Sales	40,231	0.245	0.233	0.238
Cash flow/Sales	40,231	0.177	0.164	0.154
PPE/Assets	40,231	0.253	0.262	0.142
Interest Expense/EBITDA	40,231	0.013	0.010	0.011
Debt/Assets	40,231	0.336	0.175	0.334
Cash/Assets Squared	40,231	0.030	0.051	0.008
EBITDA/Assets Squared	40,231	0.025	0.162	0.013
Cash flow/Assets Squared	40,231	0.011	0.015	0.007
EBITDA/Sales Squared	40,231	0.114	0.515	0.057
Cash flow/Sales Squared	40,231	0.058	0.103	0.030
PPE/Assets Squared	40,231	0.133	0.205	0.020
Interest Expense/EBITDA Squared	40,231	0.0003	0.001	0.0001
Debt/Assets Squared	40,231	0.144	0.153	0.111

Notes. This table presents the descriptive statistics of credit ratings, the number of severe negative ESG-related news events in the 12 months leading up to a credit rating assignment, the ratings on E/S/G performance and carbon emissions scores, and firm characteristics.

Table 3

Predicting Credit Ratings Downgrades with ESG-related Incidents

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
ESG incidents	-0.006	-0.006	0.003	0.002
	(0.009)	(0.009)	(0.007)	(0.007)
Treatment			0.252***	0.245***
			(0.033)	(0.033)
ESG Incidents x Treatment			-0.014	-0.011
			(0.014)	(0.014)
ESG Incidents x Post1			-0.016***	-0.016***
			(0.007)	(0.007)
ESG Incidents x Post2			0.008	0.007
			(0.027)	(0.027)
Treatment x Post1			-0.050	-0.048
			(0.040)	(0.041)
Treatment x Post2			-0.164***	-0.156***
			(0.055)	(0.054)
ESG Incidents x Treatment x Post1			0.045	0.044
			(0.029)	(0.029)
ESG Incidents x Treatment x Post2			-0.034	-0.037
			(0.037)	(0.037)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	40,231	40,231	40,231	40,231
Adj. R^2	0.272	0.288	0.340	0.352

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *ESG incidents* is the number of severe ESG incidents over the past 12 months leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table 4

Predicting Credit Ratings Downgrades with E/S/G Incidents

	Environmental		Social		Governance	
	(1)	(2)	(3)	(4)	(5)	(6)
	Credit Rating Downgrade					
Incidents	0.031	0.033	-0.001	-0.002	0.009	0.007
	(0.022)	(0.025)	(0.013)	(0.013)	(0.022)	(0.022)
Treatment	0.251***	0.245***	0.251***	0.244***	0.253***	0.246***
	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Incidents x Treatment	-0.091	-0.076	-0.016	-0.012	-0.046	-0.037
	(0.062)	(0.061)	(0.025)	(0.026)	(0.048)	(0.049)
Incidents x Post1	-0.040	-0.041	-0.026**	-0.027*	-0.053**	-0.057**
	(0.027)	(0.028)	(0.013)	(0.014)	(0.022)	(0.025)
Incidents x Post2	0.043	0.037	0.004	0.001	0.025	0.022
	(0.106)	(0.106)	(0.056)	(0.057)	(0.084)	(0.084)
Treatment x Post1	-0.045	-0.045	-0.046	-0.044	-0.047	-0.045
	(0.037)	(0.039)	(0.039)	(0.040)	(0.041)	(0.042)
Treatment x Post2	-0.163***	-0.155***	-0.164***	-0.156***	-0.164***	-0.156***
	(0.055)	(0.054)	(0.055)	(0.054)	(0.056)	(0.054)
Incidents x Treatment x Post1	0.252**	0.234**	0.072	0.072	0.091	0.090
	(0.098)	(0.099)	(0.061)	(0.060)	(0.072)	(0.073)
Incidents x Treatment x Post2	-0.085	-0.100	-0.088	-0.092	-0.095	-0.104
	(0.150)	(0.147)	(0.078)	(0.077)	(0.113)	(0.113)
Controls?	No	Yes	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,231	40,231	40,231	40,231	40,231	40,231
Adj. R^2	0.341	0.353	0.340	0.352	0.340	0.352

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Incidents* is the number of severe environmental (Columns 1 and 2), social (Columns 3 and 4), or governance (Columns 5 and 6) incidents over the past 12 months leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table 5

Predicting Credit Ratings with E/S/G Ratings

	Environmental		Social		Governance	
	(1)	(2)	(3)	(4)	(5)	(6)
	Credit Rating					
E/S/G Rating	-0.027	-0.008	-0.006	0.012	-0.005	-0.007
	(0.027)	(0.025)	(0.023)	(0.021)	(0.014)	(0.013)
Treatment	0.149	0.045	0.213	0.141	-0.510**	-0.516**
	(0.217)	(0.182)	(0.192)	(0.192)	(0.225)	(0.217)
E/S/G Rating x Treatment	-0.049	-0.035	-0.090**	-0.077*	0.066*	0.062*
	(0.035)	(0.031)	(0.044)	(0.044)	(0.036)	(0.033)
E/S/G Rating x Post1	-0.012	-0.050**	0.003	-0.017	-0.005	-0.005
	(0.021)	(0.021)	(0.023)	(0.022)	(0.027)	(0.021)
E/S/G Rating x Post2	-0.007	-0.027	-0.071	-0.031	-0.074	-0.116**
	(0.037)	(0.032)	(0.058)	(0.050)	(0.063)	(0.057)
Treatment x Post1	-1.061***	-0.717**	-0.921***	-0.761***	0.087	0.225
	(0.371)	(0.284)	(0.262)	(0.241)	(0.392)	(0.391)
Treatment x Post2	-0.610*	-0.514*	-0.732**	-0.592**	-0.294	-0.291
	(0.319)	(0.272)	(0.292)	(0.286)	(0.459)	(0.432)
E/S/G Rating x Treatment x Post1	0.112**	0.071	0.130**	0.120**	-0.093	-0.097
	(0.053)	(0.045)	(0.055)	(0.057)	(0.085)	(0.078)
E/S/G Rating x Treatment x Post2	0.050	0.041	0.104*	0.081	-0.001	0.009
	(0.051)	(0.045)	(0.063)	(0.063)	(0.081)	(0.078)
Controls?	No	Yes	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,280	37,280	37,280	37,280	37,280	37,280
Adj. R^2	0.922	0.937	0.922	0.937	0.922	0.937

Notes. This table reports the estimation results of regressions where the dependent variable is the bond credit rating assigned during the time period 2012-2019. *E/S/G Rating* is the most recent environmental (Columns 1 and 2), social (Columns 3 and 4), or governance (Columns 5 and 6) rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table 6

Predicting Credit Ratings with Carbon Footprint

	(1)	(2)	(3)	(4)
	Credit Rating			
Carbon	0.038	0.002	0.017	-0.005
	(0.033)	(0.028)	(0.032)	(0.028)
Treatment			-0.091	-0.270
			(0.244)	(0.208)
Carbon x Treatment			-0.009	0.012
			(0.033)	(0.030)
Carbon x Post1			0.013	-0.046*
			(0.025)	(0.026)
Carbon x Post2			0.045	-0.008
			(0.038)	(0.031)
Treatment x Post1			-2.050***	-1.568***
			(0.483)	(0.363)
Treatment x Post2			-1.020***	-0.840***
			(0.368)	(0.341)
Carbon x Treatment x Post1			0.211***	0.159***
			(0.055)	(0.044)
Carbon x Treatment x Post2			0.084**	0.066
			(0.043)	(0.041)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	36,274	36,274	36,274	36,274
Adj. R^2	0.911	0.928	0.918	0.932

Notes. This table reports the estimation results of regressions where the dependent variable is the bond credit rating assigned during the time period 2012-2019. *Carbon* is the most recent MSCI carbon emissions score leading up to the rating assignment. Higher scores reflect lower carbon emissions. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table 7

No Improvement in the Ability for Credit Ratings to Predict 2-Year Default

	(1)	(2)	(3)	(4)	(5)	(6)
	2-Year Default					
Credit Rating	-0.006**	-0.008*	-0.008*	-0.007	-0.005	-0.005
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Treatment					0.140**	0.110**
					(0.066)	(0.046)
Credit Rating x Post					0.002	0.002
					(0.002)	(0.002)
Credit Rating x Treatment					-0.009**	-0.007**
					(0.004)	(0.003)
Treatment x Post					-0.055	-0.073
					(0.047)	(0.047)
Credit Rating x Treatment x Post					0.004	0.005
					(0.003)	(0.003)
Constant	0.102**					
	(0.046)					
Controls?	No	No	No	Yes	No	Yes
Year FE?	No	No	Yes	Yes	Yes	Yes
Industry FE?	No	Yes	Yes	Yes	Yes	Yes
Observations	34,523	34,523	34,523	34,523	34,523	34,523
Adj. R^2	0.063	0.284	0.285	0.425	0.306	0.440

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for whether there is a bond default over the next 730 days after a bond rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch during the time period 2012-2017. *Post* is equal to 1 if the rating assignment took place in the years 2016-2017 and 0 otherwise. Standard errors, clustered by three-digit SIC industry codes, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table 8

Stock Market Response to Rating Downgrades

Panel A: Stock Price	(1)	(2)	(3)	(4)	(5)	(6)
	[-1,+1]	[-1,+1]	[-2,+2]	[-2,+2]	[-3,+3]	[-3,+3]
Treatment x Post	0.001	0.001	0.011	0.010	0.009	0.009
	(0.014)	(0.010)	(0.014)	(0.011)	(0.015)	(0.013)
Treatment	0.006	0.007	0.004	0.003	0.004	0.002
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)
Controls?	No	Yes	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	706	615	706	615	706	615
Adj. R^2	0.007	0.091	0.016	0.111	0.016	0.083
Panel B: Trading Volume	(1)	(2)	(3)	(4)	(5)	(6)
	[-1,+1]	[-1,+1]	[-2,+2]	[-2,+2]	[-3,+3]	[-3,+3]
Treatment x Post	-0.007	-0.002	-0.003	0.000	0.009	0.011
	(0.016)	(0.011)	(0.019)	(0.015)	(0.026)	(0.025)
Treatment	0.008	0.009	0.004	0.004	-0.005	-0.008
	(0.008)	(0.007)	(0.011)	(0.011)	(0.020)	(0.024)
Controls?	No	Yes	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	706	615	706	615	706	615
Adj. R^2	0.003	0.080	0.001	0.062	0.001	0.039

Notes. This table reports the estimation results of regressions where the dependent variables are stock market responses as indicated by the absolute cumulative abnormal return (Panel A) and cumulative abnormal trading volume (Panel B) over various short-term announcement windows around rating downgrades during the time period 2012-2017. *Treatment* is equal to 1 if the rating downgrade is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post* is equal to 1 if the rating downgrade took place after 2015. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table 9

CDS Spreads in Response to Rating Downgrades

	(1)	(2)	(3)	(4)	(5)	(6)
	[-1,+1]	[-1,+1]	[-2,+2]	[-2,+2]	[-3,+3]	[-3,+3]
Treatment x Post	12.686*	14.077*	13.826	13.764	20.665**	16.561*
	(7.490)	(7.303)	(10.336)	(9.589)	(8.745)	(9.548)
Treatment	5.171	0.812	7.966	3.719*	2.020	6.454*
	(4.562)	(1.530)	(7.174)	(2.030)	(4.145)	(3.734)
Controls?	No	Yes	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364	332	364	332	364	332
Adj. R^2	0.002	0.597	0.001	0.684	0.012	0.079

Notes. This table reports the estimation results of regressions where the dependent variable is the change in credit default swap (CDS) spreads, in basis points, over various short-term announcement windows around rating downgrades during the time period 2012-2017. *Treatment* is equal to 1 if the rating downgrade is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post* is equal to 1 if the rating downgrade took place after 2015. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

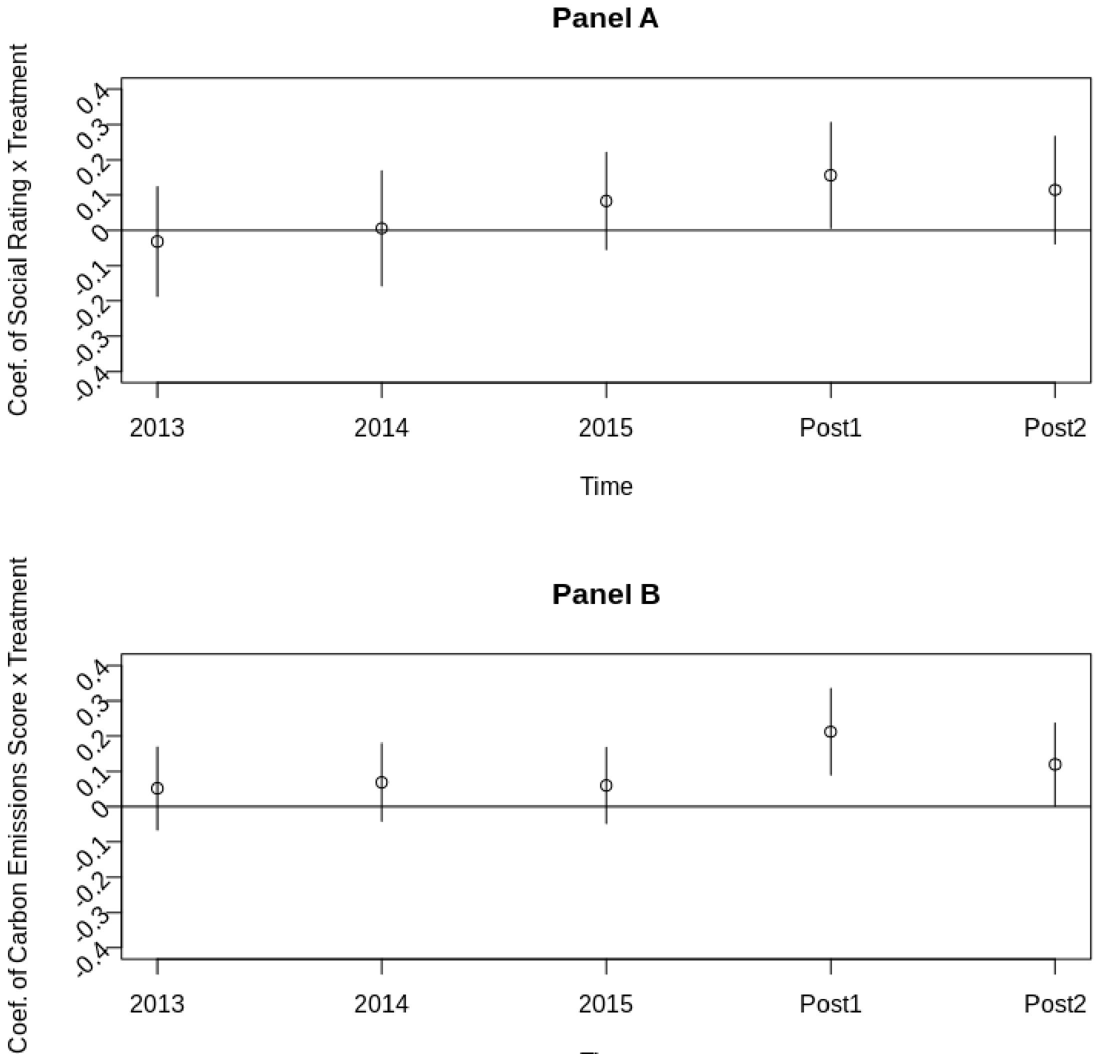

FIGURE 1

Dynamic Effects of Social Rating and Carbon Emissions Score

This figure plots the dynamic impact of social rating (Panel A) and carbon emissions score (Panel B) on credit ratings in the years leading up to ESG adoption by Moody's and S&P. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. The vertical bars denote 90% confidence intervals. Standard errors are clustered at the firm level.

Appendix

1. Predicting 1-year Ahead Default

Table A.1

No Improvement in the Ability for Credit Ratings to Predict 1-Year Default

	(1)	(2)	(3)	(4)	(5)	(6)
	1-Year Default					
Credit Rating	-0.005**	-0.007**	-0.008**	-0.006	-0.005	-0.005
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Treatment					0.097**	0.066**
					(0.042)	(0.033)
Credit Rating x Post					0.001	0.001
					(0.001)	(0.002)
Credit Rating x Treatment					-0.007**	-0.005**
					(0.003)	(0.002)
Treatment x Post					-0.011	-0.039
					(0.057)	(0.041)
Credit Rating x Treatment x Post					0.001	0.003
					(0.004)	(0.003)
Constant	0.079**					
	(0.035)					
Controls?	No	No	No	Yes	No	Yes
Year FE?	No	No	Yes	Yes	Yes	Yes
Industry FE?	No	Yes	Yes	Yes	Yes	Yes
Observations	34,523	34,523	34,523	34,523	34,523	34,523
Adj. R^2	0.056	0.198	0.198	0.368	0.214	0.375

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for whether there is a bond default over the next 365 days after a bond rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch during the time period 2012-2017. *Post* is equal to 1 if the rating assignment took place in the years 2016-2017 and 0 otherwise. Standard errors, clustered by three-digit SIC industry codes, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

2. Predicting Credit Ratings with E/S/G Incidents

Table A.2

Predicting Credit Ratings with E/S/G Incidents

	Environmental		Social		Governance	
	(1)	(2)	(3)	(4)	(5)	(6)
	Credit Rating					
Incidents	-0.021	-0.061	-0.081	-0.084*	-0.145	-0.114*
	(0.086)	(0.088)	(0.058)	(0.051)	(0.095)	(0.069)
Treatment	-0.166	-0.187*	-0.165	-0.191*	-0.157	-0.184*
	(0.109)	(0.106)	(0.107)	(0.105)	(0.108)	(0.106)
Incidents x Treatment	0.136	0.130	-0.182	-0.171	-0.520***	-0.527***
	(0.225)	(0.223)	(0.192)	(0.194)	(0.132)	(0.136)
Incidents x Post1	-0.069	0.031	0.048	0.041	0.151	0.091
	(0.089)	(0.078)	(0.045)	(0.033)	(0.104)	(0.070)
Incidents x Post2	0.073	0.119	0.073	0.054	0.125	0.092
	(0.163)	(0.165)	(0.111)	(0.118)	(0.130)	(0.126)
Treatment x Post1	-0.413***	-0.289***	-0.427***	-0.304***	-0.417***	-0.302***
	(0.127)	(0.108)	(0.128)	(0.107)	(0.130)	(0.109)
Treatment x Post2	-0.293**	-0.236**	-0.304**	-0.245**	-0.319**	-0.260**
	(0.123)	(0.112)	(0.123)	(0.113)	(0.124)	(0.114)
Incidents x Treatment x Post1	0.371	0.355	0.237	0.222*	0.317	0.309
	(0.315)	(0.300)	(0.150)	(0.128)	(0.251)	(0.237)
Incidents x Treatment x Post2	0.309	0.260	0.295	0.247	0.486	0.391
	(0.339)	(0.357)	(0.258)	(0.268)	(0.337)	(0.311)
Controls?	No	Yes	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,231	40,231	40,231	40,231	40,231	40,231
Adj. R^2	0.924	0.937	0.924	0.937	0.924	0.937

Notes. This table reports the estimation results of regressions where the dependent variable is the bond credit rating assigned during the time period 2012-2019. *Incidents* is the number of severe environmental (Columns 1 and 2), social (Columns 3 and 4), or governance (Columns 5 and 6) incidents over the past 12 months leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

3. Predicting Credit Ratings with Alternative Rater

Table A.3

Predicting Credit Ratings with Environmental Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating			
Sust. Env. Rating	0.008	0.006	0.005	0.003
	(0.006)	(0.005)	(0.006)	(0.005)
Treatment			-0.417	-0.458
			(0.378)	(0.382)
Sust. Env. Rating x Treatment			0.005	0.003
			(0.006)	(0.006)
Sust. Env. Rating x Post1			-0.003	-0.003
			(0.003)	(0.003)
Sust. Env. Rating x Post2			-0.004	-0.002
			(0.004)	(0.004)
Treatment x Post1			-1.455***	-1.247***
			(0.439)	(0.419)
Treatment x Post2			-0.381	-0.240
			(0.448)	(0.425)
Sust. Env. Rating x Treatment x Post1			0.020**	0.015*
			(0.009)	(0.008)
Sust. Env. Rating x Treatment x Post2			0.004	0.002
			(0.006)	(0.005)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.919	0.932	0.922	0.935

Notes. This table reports the estimation results of regressions where the dependent variable is the bond credit rating assigned during the time period 2012-2019. *Sust. Env. Rating* is the most recent Sustainalytics environmental rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.4

Predicting Credit Ratings with Social Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating			
Sust. Soc. Rating	0.008	0.016**	0.006	0.005
	(0.008)	(0.008)	(0.008)	(0.008)
Treatment			-0.287	-0.325
			(0.619)	(0.608)
Sust. Soc. Rating x Treatment			0.003	0.002
			(0.009)	(0.009)
Sust. Soc. Rating x Post1			0.005	0.010**
			(0.005)	(0.005)
Sust. Soc. Rating x Post2			0.002	0.008
			(0.007)	(0.005)
Treatment x Post1			-1.232**	-1.287**
			(0.601)	(0.591)
Treatment x Post2			-0.371	-0.021
			(0.685)	(0.634)
Sust. Soc. Rating x Treatment x Post1			0.018*	0.019*
			(0.010)	(0.010)
Sust. Soc. Rating x Treatment x Post2			0.004	-0.004
			(0.010)	(0.009)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.919	0.933	0.922	0.935

Notes. This table reports the estimation results of regressions where the dependent variable is the bond credit rating assigned during the time period 2012-2019. *Sust. Soc. Rating* is the most recent Sustainalytics social rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.5

Predicting Credit Ratings with Governance Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating			
Sust. Gov. Rating	0.005	0.009*	0.005	0.009*
	(0.005)	(0.005)	(0.005)	(0.006)
Treatment			-0.946	-0.825
			(0.638)	(0.641)
Sust. Gov. Rating x Treatment			0.014	0.010
			(0.010)	(0.010)
Sust. Gov. Rating x Post1			-0.007	-0.003
			(0.003)	(0.003)
Sust. Gov. Rating x Post2			-0.008	-0.004
			(0.006)	(0.006)
Treatment x Post1			-0.217	-0.065
			(0.788)	(0.815)
Treatment x Post2			0.664	0.675
			(0.926)	(0.918)
Sust. Gov. Rating x Treatment x Post1			-0.004	-0.003
			(0.011)	(0.011)
Sust. Gov. Rating x Treatment x Post2			-0.012	-0.011
			(0.013)	(0.013)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.920	0.934	0.924	0.936

Notes. This table reports the estimation results of regressions where the dependent variable is the bond credit rating assigned during the time period 2012-2019. *Sust. Gov. Rating* is the most recent Sustainalytics governance rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

4. Predicting Credit Rating Downgrades with E/S/G Ratings

Table A.6

Predicting Credit Ratings Downgrades with Environmental Ratings

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
Env. Rating	-0.013*	-0.013*	-0.010	-0.011
	(0.007)	(0.007)	(0.007)	(0.008)
Treatment			0.220***	0.202***
			(0.077)	(0.077)
Env. Rating x Treatment			0.003	0.005
			(0.013)	(0.013)
Env. Rating x Post1			-0.011*	-0.007
			(0.006)	(0.007)
Env. Rating x Post2			-0.002	0.006
			(0.011)	(0.012)
Treatment x Post1			-0.031	-0.022
			(0.100)	(0.106)
Treatment x Post2			-0.210*	-0.206*
			(0.108)	(0.106)
Env. Rating x Treatment x Post1			-0.003	-0.003
			(0.018)	(0.018)
Env. Rating x Treatment x Post2			0.007	0.007
			(0.018)	(0.017)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	37,280	37,280	37,280	37,280
Adj. R^2	0.278	0.292	0.340	0.350

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Env. Rating* is the most recent MSCI environmental rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.7

Predicting Credit Ratings Downgrades with Social Ratings

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
Soc. Rating	0.008	0.009	0.001	0.002
	(0.008)	(0.007)	(0.007)	(0.007)
Treatment			0.167***	0.164***
			(0.062)	(0.061)
Soc. Rating x Treatment			0.017	0.017
			(0.014)	(0.014)
Soc. Rating x Post1			-0.002	-0.007
			(0.008)	(0.009)
Soc. Rating x Post2			0.015	0.015
			(0.019)	(0.019)
Treatment x Post1			-0.098	-0.112
			(0.089)	(0.092)
Treatment x Post2			-0.032	-0.025
			(0.115)	(0.113)
Soc. Rating x Treatment x Post1			0.014	0.018
			(0.019)	(0.019)
Soc. Rating x Treatment x Post2			-0.033	-0.034
			(0.025)	(0.025)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	37,280	37,280	37,280	37,280
Adj. R^2	0.277	0.291	0.340	0.351

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Soc. Rating* is the most recent MSCI social rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.8

Predicting Credit Ratings Downgrades with Governance Ratings

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
Gov. Rating	0.001	0.002	0.004	0.006
	(0.006)	(0.006)	(0.005)	(0.005)
Treatment			0.299***	0.299***
			(0.076)	(0.075)
Gov. Rating x Treatment			-0.011	-0.012
			(0.011)	(0.011)
Gov. Rating x Post1			0.016	0.020
			(0.010)	(0.013)
Gov. Rating x Post2			0.003	0.001
			(0.020)	(0.020)
Treatment x Post1			0.028	0.041
			(0.097)	(0.099)
Treatment x Post2			-0.308	-0.289
			(0.200)	(0.198)
Gov. Rating x Treatment x Post1			-0.018	-0.021
			(0.017)	(0.018)
Gov. Rating x Treatment x Post2			0.025	0.023
			(0.034)	(0.034)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	37,280	37,280	37,280	37,280
Adj. R^2	0.277	0.291	0.339	0.351

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Gov. Rating* is the most recent MSCI governance rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.9

Predicting Credit Ratings Downgrades with Carbon Footprint

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
Carbon	-0.012	-0.013	-0.007	-0.009
	(0.008)	(0.008)	(0.008)	(0.008)
Treatment			0.216**	0.211**
			(0.093)	(0.093)
Carbon x Treatment			0.003	0.003
			(0.011)	(0.011)
Carbon x Post1			-0.015**	-0.013
			(0.007)	(0.009)
Carbon x Post2			-0.007	-0.006
			(0.013)	(0.014)
Treatment x Post1			0.073	0.080
			(0.137)	(0.145)
Treatment x Post2			-0.247	-0.271*
			(0.155)	(0.151)
Carbon x Treatment x Post1			-0.017	-0.017
			(0.016)	(0.017)
Carbon x Treatment x Post2			0.008	0.011
			(0.018)	(0.017)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	36,274	36,274	36,274	36,274
Adj. R^2	0.281	0.297	0.348	0.359

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Carbon* is the most recent MSCI carbon emissions score leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.10

Predicting Credit Ratings Downgrades with Environmental Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
Sust. Env. Rating	-0.003	-0.003	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment			0.014	-0.005
			(0.130)	(0.129)
Sust. Env. Rating x Treatment			0.004	0.004
			(0.003)	(0.003)
Sust. Env. Rating x Post1			-0.002**	-0.002**
			(0.001)	(0.001)
Sust. Env. Rating x Post2			0.000	0.000
			(0.002)	(0.002)
Treatment x Post1			0.266	0.251
			(0.185)	(0.181)
Treatment x Post2			0.030	0.029
			(0.233)	(0.222)
Sust. Env. Rating x Treatment x Post1			-0.004	-0.003
			(0.003)	(0.003)
Sust. Env. Rating x Treatment x Post2			-0.002	-0.002
			(0.003)	(0.003)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.251	0.270	0.325	0.345

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Sust. Env. Rating* is the most recent Sustainalytics environmental rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.11

Predicting Credit Rating Downgrades with Social Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
Sust. Soc. Rating	-0.003	-0.004	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Treatment			0.209	0.187
			(0.207)	(0.206)
Sust. Soc. Rating x Treatment			0.002	0.002
			(0.003)	(0.003)
Sust. Soc. Rating x Post1			-0.003*	-0.004**
			(0.002)	(0.002)
Sust. Soc. Rating x Post2			-0.002	-0.003
			(0.003)	(0.003)
Treatment x Post1			-0.287	-0.228
			(0.245)	(0.247)
Treatment x Post2			-0.240	-0.233
			(0.274)	(0.268)
Sust. Soc. Rating x Treatment x Post1			0.004	0.003
			(0.003)	(0.003)
Sust. Soc. Rating x Treatment x Post2			0.002	0.002
			(0.004)	(0.004)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.251	0.273	0.325	0.341

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Sust. Soc. Rating* is the most recent Sustainalytics social rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.12

Predicting Credit Rating Downgrades with Governance Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating Downgrade			
Sust. Gov. Rating	-0.002	-0.002	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment			0.303	0.289
			(0.229)	(0.227)
Sust. Gov. Rating x Treatment			-0.002	-0.002
			(0.003)	(0.003)
Sust. Gov. Rating x Post1			0.002	0.002*
			(0.001)	(0.001)
Sust. Gov. Rating x Post2			-0.000	0.000
			(0.002)	(0.002)
Treatment x Post1			0.133	0.130
			(0.282)	(0.287)
Treatment x Post2			-0.978***	-0.970**
			(0.406)	(0.405)
Sust. Gov. Rating x Treatment x Post1			-0.002	-0.002
			(0.003)	(0.003)
Sust. Gov. Rating x Treatment x Post2			0.013	0.013
			(0.008)	(0.008)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.250	0.271	0.327	0.342

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating downgrade in the time period 2012-2019. *Sust. Gov. Rating* is the most recent Sustainalytics governance rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

5. Predicting Credit Rating Upgrades

Table A.13

Predicting Credit Ratings Upgrades with Environmental Incidents

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Env. Incidents	-0.011	-0.017	0.016	0.015
	(0.017)	(0.015)	(0.026)	(0.026)
Treatment			0.242***	0.244***
			(0.027)	(0.027)
Env. Incidents x Treatment			-0.075	-0.090
			(0.070)	(0.063)
Env. Incidents x Post1			-0.033	-0.041
			(0.029)	(0.030)
Env. Incidents x Post2			-0.045	-0.046
			(0.031)	(0.033)
Treatment x Post1			-0.131***	-0.129***
			(0.031)	(0.031)
Treatment x Post2			-0.147***	-0.153***
			(0.039)	(0.039)
Env. Incidents x Treatment x Post1			0.098	0.117
			(0.119)	(0.115)
Env. Incidents x Treatment x Post2			-0.009	0.008
			(0.088)	(0.080)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	40,231	40,231	40,231	40,231
Adj. R^2	0.219	0.232	0.293	0.307

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Env. Incidents* is the number of severe environmental incidents over the past 12 months leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

TABLE A.14

PREDICTING CREDIT RATINGS UPGRADES WITH SOCIAL INCIDENTS

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Soc. Incidents	0.005	0.001	0.009	0.007
	(0.008)	(0.008)	(0.008)	(0.009)
Treatment			0.243***	0.245***
			(0.027)	(0.026)
Soc. Incidents x Treatment			-0.031***	-0.034***
			(0.012)	(0.011)
Soc. Incidents x Post1			-0.006	-0.010
			(0.006)	(0.007)
Soc. Incidents x Post2			-0.039	-0.044
			(0.027)	(0.027)
Treatment x Post1			-0.137***	-0.135***
			(0.030)	(0.031)
Treatment x Post2			-0.150***	-0.156***
			(0.039)	(0.039)
Soc. Incidents x Treatment x Post1			0.078	0.083
			(0.063)	(0.063)
Soc. Incidents x Treatment x Post2			-0.015	-0.008
			(0.034)	(0.032)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	40,231	40,231	40,231	40,231
Adj. R^2	0.219	0.232	0.294	0.308

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Soc. Incidents* is the number of severe social incidents over the past 12 months leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.15

Predicting Credit Ratings Upgrades with Governance Incidents

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Gov. Incidents	0.014	0.006	0.035**	0.033*
	(0.010)	(0.010)	(0.016)	(0.017)
Treatment			0.245***	0.247***
			(0.027)	(0.027)
Gov. Incidents x Treatment			-0.079***	-0.084***
			(0.024)	(0.023)
Gov. Incidents x Post1			-0.026	-0.036*
			(0.017)	(0.019)
Gov. Incidents x Post2			-0.047	-0.053
			(0.036)	(0.037)
Treatment x Post1			-0.135***	-0.135***
			(0.031)	(0.032)
Treatment x Post2			-0.152***	-0.158***
			(0.039)	(0.039)
Gov. Incidents x Treatment x Post1			0.110	0.118*
			(0.069)	(0.070)
Env. Incidents x Treatment x Post2			0.018	0.027
			(0.044)	(0.041)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	40,231	40,231	40,231	40,231
Adj. R^2	0.219	0.232	0.294	0.308

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Gov. Incidents* is the number of severe governance incidents over the past 12 months leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.16

Predicting Credit Ratings Upgrades with Environmental Ratings

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Env. Rating	0.000	-0.000	0.005	0.006
	(0.006)	(0.005)	(0.005)	(0.005)
Treatment			0.256***	0.267***
			(0.074)	(0.073)
Env. Rating x Treatment			-0.003	-0.005
			(0.012)	(0.011)
Env. Rating x Post1			-0.008*	-0.011**
			(0.004)	(0.004)
Env. Rating x Post2			-0.003	-0.002
			(0.007)	(0.007)
Treatment x Post1			-0.118	-0.118
			(0.085)	(0.087)
Treatment x Post2			-0.117	-0.126
			(0.110)	(0.108)
Env. Rating x Treatment x Post1			-0.002	-0.001
			(0.013)	(0.014)
Env. Rating x Treatment x Post2			-0.006	-0.006
			(0.018)	(0.018)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	37,280	37,280	37,280	37,280
Adj. R^2	0.224	0.238	0.296	0.311

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Env. Rating* is the most recent MSCI environmental rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.17

Predicting Credit Ratings Upgrades with Social Ratings

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Soc. Rating	0.006	0.007	0.001	0.002
	(0.006)	(0.007)	(0.005)	(0.005)
Treatment			0.151**	0.152**
			(0.061)	(0.059)
Soc. Rating x Treatment			0.022*	0.022*
			(0.013)	(0.013)
Soc. Rating x Post1			-0.008	-0.009*
			(0.005)	(0.005)
Soc. Rating x Post2			0.011	0.006
			(0.012)	(0.012)
Treatment x Post1			-0.080	-0.084
			(0.073)	(0.075)
Treatment x Post2			0.049	0.035
			(0.105)	(0.105)
Soc. Rating x Treatment x Post1			-0.012	-0.010
			(0.017)	(0.017)
Soc. Rating x Treatment x Post2			-0.050**	-0.047**
			(0.022)	(0.022)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	37,280	37,280	37,280	37,280
Adj. R^2	0.225	0.239	0.299	0.313

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Soc. Rating* is the most recent MSCI social rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.18

Predicting Credit Ratings Upgrades with Governance Ratings

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Gov. Rating	0.007**	0.005*	0.002	0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Treatment			0.125**	0.117**
			(0.059)	(0.058)
Gov. Rating x Treatment			0.020**	0.022**
			(0.010)	(0.010)
Gov. Rating x Post1			0.006	0.008
			(0.006)	(0.006)
Gov. Rating x Post2			-0.007	0.003
			(0.019)	(0.018)
Treatment x Post1			-0.053	-0.044
			(0.078)	(0.080)
Treatment x Post2			-0.229	-0.222
			(0.149)	(0.141)
Gov. Rating x Treatment x Post1			-0.011	-0.012
			(0.015)	(0.015)
Gov. Rating x Treatment x Post2			-0.015	-0.013
			(0.027)	(0.026)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	37,280	37,280	37,280	37,280
Adj. R^2	0.226	0.239	0.301	0.316

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Gov. Rating* is the most recent MSCI governance rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.19

Predicting Credit Ratings Upgrades with Carbon Footprint

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Carbon	-0.009	-0.009	-0.002	-0.000
	(0.006)	(0.006)	(0.006)	(0.006)
Treatment			0.394***	0.409***
			(0.085)	(0.084)
Carbon x Treatment			-0.019*	-0.021**
			(0.010)	(0.010)
Carbon x Post1			-0.006	-0.013***
			(0.005)	(0.005)
Carbon x Post2			-0.014	-0.010
			(0.010)	(0.010)
Treatment x Post1			-0.231**	-0.257**
			(0.111)	(0.115)
Treatment x Post2			-0.182	-0.185
			(0.143)	(0.138)
Carbon x Treatment x Post1			0.013	0.016
			(0.013)	(0.013)
Carbon x Treatment x Post2			0.004	0.004
			(0.016)	(0.016)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	36,274	36,274	36,274	36,274
Adj. R^2	0.222	0.234	0.300	0.313

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Carbon* is the most recent MSCI carbon emissions score leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.20

Predicting Credit Ratings Upgrades with Environmental Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Sust. Env. Rating	-0.002	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment			0.346***	0.372***
			(0.120)	(0.116)
Sust. Env. Rating x Treatment			-0.002	-0.002
			(0.002)	(0.002)
Sust. Env. Rating x Post1			-0.000	-0.000
			(0.001)	(0.001)
Sust. Env. Rating x Post2			-0.001	-0.001
			(0.001)	(0.001)
Treatment x Post1			-0.146	-0.140
			(0.148)	(0.149)
Treatment x Post2			-0.152	-0.124
			(0.181)	(0.179)
Sust. Env. Rating x Treatment x Post1			0.000	0.000
			(0.001)	(0.001)
Sust. Env. Rating x Treatment x Post2			-0.000	-0.001
			(0.002)	(0.002)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.201	0.212	0.284	0.297

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Sust. Env. Rating* is the most recent Sustainalytics environmental rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.21

Predicting Credit Ratings Upgrades with Social Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Sust. Soc. Rating	0.001	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Treatment			-0.007	-0.008
			(0.171)	(0.172)
Sust. Soc. Rating x Treatment			0.004	0.004
			(0.003)	(0.003)
Sust. Soc. Rating x Post1			0.000	0.001
			(0.001)	(0.001)
Sust. Soc. Rating x Post2			-0.003	-0.003
			(0.002)	(0.002)
Treatment x Post1			-0.010	-0.019
			(0.198)	(0.202)
Treatment x Post2			0.098	0.117
			(0.248)	(0.247)
Sust. Soc. Rating x Treatment x Post1			-0.002	-0.002
			(0.003)	(0.004)
Sust. Soc. Rating x Treatment x Post2			-0.003	-0.004
			(0.004)	(0.004)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.203	0.215	0.283	0.298

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Sust. Soc. Rating* is the most recent Sustainalytics social rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.

Table A.22

Predicting Credit Ratings Upgrades with Governance Ratings From Sustainalytics

	(1)	(2)	(3)	(4)
	Credit Rating Upgrade			
Sust. Gov. Rating	0.001	0.001	-0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment			-0.000	0.001
			(0.196)	(0.189)
Sust. Gov. Rating x Treatment			0.004	0.004
			(0.003)	(0.003)
Sust. Gov. Rating x Post1			0.002**	0.002**
			(0.001)	(0.001)
Sust. Gov. Rating x Post2			0.001	0.001
			(0.002)	(0.002)
Treatment x Post1			-0.115	-0.116
			(0.233)	(0.231)
Treatment x Post2			0.403	0.416
			(0.303)	(0.302)
Sust. Gov. Rating x Treatment x Post1			-0.000	-0.000
			(0.003)	(0.003)
Sust. Gov. Rating x Treatment x Post2			-0.008*	-0.008*
			(0.005)	(0.005)
Controls?	No	Yes	No	Yes
Year FE?	Yes	Yes	Yes	Yes
Bond FE?	Yes	Yes	Yes	Yes
Observations	35,243	35,243	35,243	35,243
Adj. R^2	0.203	0.212	0.285	0.297

Notes. This table reports the estimation results of regressions where the dependent variable is a dummy variable for rating upgrade in the time period 2012-2019. *Sust. Gov. Rating* is the most recent Sustainalytics governance rating leading up to the rating assignment. *Treatment* is equal to 1 if the rating assignment is issued by either Moody's or S&P and 0 if it is issued by Fitch. *Post1* (*Post2*) is equal to 1 if the rating assignment took place in the years 2016-2017 (2018-2019) and 0 otherwise. Standard errors, clustered by firm, are reported in parentheses. Significance at the ten percent level is given by *; at the five percent level **, at the one percent level ***.