Do Employees Have Useful Information About Firms' ESG Practices?

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Abstract

This study evaluates whether employees have useful information about firms' ESG (Environmental, Social, Governance) practices. Analyzing 10 million employee reviews, it reveals that 43% of employees discuss ESG topics, with governance surprisingly receiving the most attention. Employees' ESG inside view outperforms existing ESG ratings in predicting many hard-to-manipulate outcomes on all ESG categories, as well as valuation, downside risk, and stock return. Moreover, the inside view appears robust to greenwashing, as low-cost changes in a firm's ESG commitment do not affect it, while costlier changes do. Thus, incorporating employee perspectives can significantly enhance ESG investing for investors and rating agencies.

Keywords: ESG, CSR, informativeness, ratings, greenwash, cheap talk, employees, NLP, Glassdoor.
JEL Classification: G30, G34, M14, M40, D22.

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1. Introduction

ESG investing, or investing with environmental, social, and governance criteria, has become mainstream (Edmans (2023)). Given the trillions of dollars under ESG investing, investors have been calling for better information and better ratings of companies' ESG practices.[1] However, the existing ESG ratings from external providers often rely on a firm's voluntary disclosure, in which the firm has both the ability and the incentive to appear ESG-friendly. Consequently, outside views of a firm's ESG practices like the existing ratings are subject to a corporate greenwashing bias, i.e., ESG cheap talk.

An alternative to assessing a firm's ESG practices from an outside view is to do so from an inside view. A firm's employees often write anonymous reviews about the firm on public platforms like Glassdoor.com or CareerBuilder.com. Since these reviews are anonymous, they are likely less prone to a greenwashing bias than corporate voluntary disclosures. In addition, prior research has shown that employees have significant information about firms' financial performance (Sheng (2022)) and employee satisfaction predicts firm value (Edmans (2011), Green et al. (2019)), so employees may have useful information about firms' ESG performance too. Thus, in this paper, I examine whether a firm's employees actually have useful information about its ESG practices. Specifically, I study whether employees have information beyond the existing ESG ratings, and whether their information is affected by greenwashing, or ESG cheap talk.

Theoretically, it is unclear whether employees have information beyond the existing ESG ratings. Employees may not provide such information because they do not care about ESG issues, or they simply listen to firm disclosures. This possibility is more likely for the environmental (E) category, but less likely for the social (S) category, as social issues like working conditions affect employee welfare directly (e.g., Bonelli, Brière, and Derrien (2022)). Employees may also know about governance (G) issues, as they regularly observe a firm's governance practices like communication, compliance, and ethics. However, the relative importance of the E, S, and G categories for employees remains an open question, as Colonnelli et al. (2023) find that prospective Brazilian employees care more about E issues than S and G issues in hypothetical job postings.

Whether employees' information is affected by corporate greenwashing, is another open empirical question. On the one hand, anonymity may allow employees to share information without fears. For

[1] For example: https://www.sec.gov/news/speech/lizarraga-speech-meeting-investor-demand-high-quality-esg-data

example, Hacamo (2022) shows that employees do complain about workplace racism on anonymous job sites and such complaints negatively affect firm performance. On the other hand, employees may still have an incentive to greenwash the firm's image, for better career prospects with the firm. Additionally, a firm may manipulate reviews to make them appear more rosy (e.g., Mayzlin, Dover, and Chevalier (2014)).

To evaluate these hypotheses, I extract ESG content from 10.4 million anonymous employee reviews on Glassdoor, a leading employer rating platform, using a machine learning approach as in Li et al. (2021). I find that 43% of reviews mention at least one ESG key word, suggesting that employees do care about ESG issues. They pay more attention to S issues than E issues, with 22% of reviews mentioning S issues, compared to only 2% for E issues. Surprisingly, employees pay even more attention to G issues, with 28% of reviews mentioning a G key word. These findings are in stark contrast to Colonnelli et al. (2023)'s finding that Brazilian job seekers care more about E rather than S or G practices, but consistent with the varied preferences for ESG practices in different countries (e.g., Matos (2020)).

Despite employees' lower attention to E issues, I find that their insights significantly predict a firm's future emissions, with or without controlling for the MSCI ESG rating, the most widely used ESG index. Moreover, consistent with employees knowing even more about S and G issues, I find that their insights on these issues substantially outperform the MSCI ESG ratings in predicting many S&G-related future outcomes for a firm. These findings hold even after controlling for the overall employee satisfaction on Glassdoor, suggesting unique value in employee insights beyond general satisfaction levels studied previously (e.g., Green et al. (2019)). The employees' ESG inside views also outperform the MSCI ratings when predicting firms' financial outcomes, namely valuation, downside risk, and stock return. These results imply that investors and rating agencies could benefit from integrating employee perspectives into ESG investing and rating processes.

Furthermore, the inside view by employees appears robust to ESG cheap talk. Across multiple settings, low-cost changes in a firm's ESG policies do not affect the inside view while more expensive changes do, such as changes driven by a court ruling as a novel exogenous shock. Finally, the inside view has a low correlation (below 0.15) with the existing ESG ratings. This low correlation suggests that corporate greenwashing may be pervasive, consistent with survey evidence that 61% of investors view greenwashing as a major obstacle for ESG investing.[2]

[2] https://securities.cib.bnpparibas/global-esg-survey-2023/global-esg-survey-2023-report/

My findings rely on capturing an inside view of ESG practices from Glassdoor reviews, which offer several advantages. First, Glassdoor is the largest employer rating website. Second, Glassdoor has many policies to ensure review quality, such as the give-to-get policy, which requires each Glassdoor user to contribute to the site before accessing its content. This policy motivates more people to write reviews, making Glassdoor reviews less prone to typical selection concerns with online reviews (Marinescu et al. (2021)). Indeed, my findings are robust to different selection concerns, as discussed in Section 6.

Moreover, each Glassdoor review has two open-ended sections in which an employee describes the pros and the cons of working at a firm. This feature allows me to capture an ESG inside view by how often a firm's employees mention ESG issues in the pros relative to the cons sections. This approach is novel. First, it removes the need for sentiment classification, a common practice in the literature (Loughran and McDonald (2016)). Second, the approach naturally differentiates positive and negative views, unlike other studies using a dictionary approach, such as Li et al. (2021), which counts words about firm culture regardless of their tone in earnings calls.

The challenge is to form comprehensive dictionaries for ESG topics that are specific to employee reviews. To tackle this challenge, I first create a seed word list for each ESG category by retaining the most frequently used words (and phrases) on the category from ESG rating methodologies and academic articles. Next, I train a machine learning model to learn the meaning of all words in 10.4 million employee reviews, using a word-embedding algorithm as in Cong, Liang, and Zhang (2019), Hanley and Hoberg (2019), Bloom et al. (2021), among others. The model allows me to extend my seed word list to the 500 most similar words in each ESG category, as in Li et al. (2021). This procedure brings my dictionaries closer to the vocabulary employees often use to describe ESG topics. For example, it adds many meaningful ESG words, such as *biofuel* and *fertilizer* to the E category, *advocacy* and *social justice* to the S category, and *malfeasance* and *embezzlement* to the G category. These dictionaries also allow me to measure each ESG category separately, and easily interpret them.

Equipped with the comprehensive ESG dictionaries, I calculate the inside view on each ESG category for each review and aggregate it to the firm-year level by averaging across reviews in each firm-year. The firm-year measures appear sensible in many aspects. First, their distributions are all bell-shaped, consistent with Glassdoor having few extreme reviews. Second, very few (under 0.2%) of all reviews exhibit an all-positive or all-negative view across the ESG categories, indicating that the reviews suffer little from a halo effect.[3] Third, consistent with the hypothesis that a firm's ESG practices are persistent, I find that the lagged ESG inside view significantly predicts itself. Finally, among the largest 500 companies by assets during 2014-2018, ranking ESG practices based on the inside view appears sensible (see Table 3). For example, a renewable energy firm was ranked first on E practices, while a large oil and gas company was ranked last.

Given the measures of employees' inside view, I investigate whether the inside view has information beyond the existing ESG ratings. Specifically, I examine whether the inside view predicts hard-to-manipulate indicators of a firm's future ESG performance, above and beyond the MSCI ESG rating, the most widely used ESG indices. [4] I focus on predictions, as Edmans (2023) argues that ESG assessments are useful if they are forward-looking. In all the predictive tests, I closely follow Li et al (2021) to control for firm size and operating performance as well as industry and year fixed effects. Doing so alleviates the concern that firms with more resources may have happier employees (better inside views) and also achieve better ESG-related outcomes, even though the firms may not care about ESG practices per se. Moreover, because existing studies have shown that the overall numerical rating on Glassdoor is informative about firms' future performance, I control for it directly to examine whether my text-based measures have additional information beyond a firm's overall employee satisfaction.

On the E category, I examine two indicators that are relatively harder to greenwash. The first indicator is a firm's total emissions, which include its Scope 3 emissions, or emissions along the firm's supply chain beyond emissions from its direct operations (Scope 1 and Scope 2 emissions), so it is harder to greenwash this indicator. Additionally, I study the indicator of whether a firm discloses Scope 3 emissions, as merely disclosing Scope 3 emissions has been shown to signal environmental responsibility and induce significant reductions in emissions along the supply chain (Cho et al. (2024)). I find that a higher inside view is associated with a significantly higher likelihood of a firm disclosing Scope 3 emissions in the future, even after controlling for the MSCI rating and the Glassdoor overall rating. In predicting a firm's total level of emissions, the inside view appears to have even more predictive power relative to the MSCI rating. These results hold after controlling additionally for a firm's governance attributes, many more firm characteristics, and any other numerical ratings on Glassdoor, as well as industry times year fixed effects. Overall, the

[3] The tendency for one's judgement of a category to influence judgement of other categories (Thorndike (1920)).

[4] I do not use the ESG ratings by Refinitiv since it frequently alters historical data (Berg, Fabisik, and Sautner (2021)).

predictive power of the inside view on the E category is remarkable, given the lower attention employees pay to E issues.

For the S category, the inside view also has significant power in predicting social outcomes that are independently validated and thus harder to greenwash. A higher S inside view significantly predicts many years ahead a higher likelihood of a firm's joining Fortune Magazine's Best 100 Companies to Work For, a list constructed from an independent survey of firms' employees. Similarly, a higher S inside view is significantly associated with a higher likelihood of a firm's landing on the Best Company for Diversity list, which is derived from an independent survey of minorities inside a firm, like women and LGBT employees. By contrast, the MSCI S rating only has significant power in predicting the Best 100 Company list, but shows no significant power in predicting the Best Diversity list. In predicting these social outcomes, the inside view's predictive power remains significant after controlling additionally for a firm's governance attributes, many more firm characteristics, all the numerical ratings on Glassdoor, as well as industry times year fixed effects, and even the lagged values of the predicted outcomes. Thus, employees appear to have substantial information about firms' practices on the S category.

For the G category, the inside view outperforms the MSCI rating even more strongly, in predicting future indicators of governance quality that are rather hard for firms to manipulate. First, a higher G inside view significantly predicts many years ahead a lower number of internal control weaknesses a firm has according to its external auditors' evaluation, while a higher MSCI G rating does not. Second, unlike the MSCI rating, the inside view significantly and negatively predicts the risk of a firm's having misstatements in its financial reporting, a measure developed by Bertomeu et al. (2021). Third, the G inside view is significantly associated with a lower number of shareholder activism events for a firm in three years ahead, while the MSCI G rating is not. These results hold after controlling for industry times year fixed effects, many firm characteristics, including financial performance ratios, corporate governance attributes, and all the numerical ratings on Glassdoor.

The employees' inside view on ESG issues has significant power beyond the MSCI ratings in predicting a firm's future financial (non-ESG) outcomes as well, but only on the S and G categories. Unlike the E inside view, the S inside view is significantly and positively associated with a firm's future valuation (Tobin's Q). A higher inside view on the G category is significantly associated with not only a firm's higher future valuation, but also a lower downside risk and a higher stock return, one, two, and even three years ahead. The economic magnitude of the inside view's predictive power is similar to or larger than that of the MSCI ESG ratings in all cases. These results are unlikely due to reverse causality because they hold when I instrument the inside view by its past values. The results remain significant when I control for industry times year fixed effects, many firm characteristics, including past performance, as well as Glassdoor's overall rating, suggesting that omitted factors related to industry trends, financial resources, and a general employee sentiment are unlikely to explain the results.[5]

Next, I investigate whether the employees' inside view is affected by corporate greenwashing, i.e., ESG cheap talk. I do so by studying two settings in which a firm shows a broad commitment to ESG policies, one without and another with a high cost of commitment. The first setting is when firms signed the Business Roundtable (BRT)'s statement in 2019 committing to serving all stakeholders rather than just shareholders. These firms did not seek the approval of their shareholders or board to sign the statement, so the BRT commitment was likely cheap talk (Bebchuk and Tallarita (2020)). The other setting is when firms join the UN Global Compact (UNGC), the world's largest corporate sustainability initiative. Unlike the BRT commitment, the UNGC commitment requires board approval and carries a likely large cost because firms must report annual progress or else get publicly expelled. Historically, the UNGC has expelled over 40% of its participants as of 2020.

If the inside view is robust to greenwashing (ESG cheap talk), then it is more likely to improve after a costly commitment like the UNGC setting, relative to a costless commitment like the BRT setting. I find that to be the case. Signing the BRT statement is not significantly associated with a larger improvement in the inside view of ESG practices. Moreover, before signing the BRT statement, BRT firms do not have a significantly better inside view. Even among firms with a prior low E, S, or G inside view, and thus more room for improvement, signing the BRT statement is associated with no significant improvement in the E inside view and even a modest decline in the S and G inside views. By contrast, the inside view on the S and G categories significantly improves three years after a firm joins the UNGC, relative to control firms.

Because I compare two different sets of firms making two different commitments, one concern is that the results may be driven by selection factors other than the cost of the ESG commitments. To alleviate this concern, I study how the employees' inside view changes after an exogenous ESG-specific shock, which raises some firms' cost of poor ESG practices while leaving others intact. Specifically, I examine a court

[5] Also, an ESG-specific shock significantly affects firm value, suggesting a causal relationship (see Section 5.3).

ruling in 2013 that unexpectedly raises the cost of poor corporate practices on an important ESG issue: workplace harassment. Before 2013, employers in the US could be held liable for workplace harassment when the harasser had a supervisory role over the victim. In 2013, however, the 7th Circuit Court, which set precedents for legal cases in Illinois, Indiana, and Wisconsin, ruled against an employer for racial and sexual harassment even when the harasser was merely a co-worker, not a supervisor, of the victim. The court ruling essentially raised the risk of harassment lawsuits and thus the incentive to improve social (S) practices for firms located in those three states (treated firms) relative to other US firms (control firms). Indeed, the S inside view increased significantly after the ruling for the treated relative to control firms. By contrast, the inside view did not improve on the E category, and even a declined on the G category. The results suggest that the inside view reflects costly within-firm changes in ESG practices, and on the correct dimension too.

After establishing that employees have an ESG inside view that is informative and robust to greenwashing, I finally examine the correlation between the inside view and existing ESG ratings. I expect it to be low, given that even within the most widely used ESG ratings, the correlation among the ratings averages at 0.54 (Berg, Koelbel, and Rigobon (2022)). The inside view' correlation with the existing ratings could be even lower if the existing ratings are affected by corporate greenwashing while the inside view is not. I find that to be the case. The correlation between the inside view and the MSCI ESG rating is 0.13 overall, and 0.00, 0.12, and 0.08 for the E, S, and G categories, respectively. The low correlation is unlikely due to measurement noise or measurement scope, as it remains low in subsamples with likely less noise and it is low for a narrow ESG issue like diversity and inclusion as well.

This paper contributes to several literatures. First, it adds to the growing literature on corporate sustainability and ESG investing (Gillan, Koch, and Starks (2021)). Matos (2020), among others, illustrates the massive growth in ESG investing, necessitating a better understanding of firms' ESG practices. Grewal and Serafeim (2020), however, emphasize that measuring firms' ESG performance is the least developed area of research. My paper addresses this issue directly. It shows that employees have information about a firm's ESG practices beyond existing ESG ratings and such information is robust to corporate greenwashing. These insights are important for investors to navigate ESG investing, for rating agencies to improve their methodologies, and for regulators and academics to evaluate corporate greenwashing.

Second, the paper contributes to the literature on the informativeness of employee reviews. Using survey data, prior studies show that employee reviews are informative about future accounting and stock return performances (e.g., Edmans (2011)). With online reviews specifically, Green et al. (2019), Sheng (2022), and Welch and Yoon (2020) show that Glassdoor reviews predict firms' future performance as well. While these prior studies show that employee reviews are informative about firms' financial performance, this paper shows that employee reviews are informative about firms' non-financial performance, namely ESG practices. These findings are not trivial, as reviews are informative even on dimensions that do not affect employee welfare directly, with surprisingly the most informativeness on the governance category.

Furthermore, my text-based inside view measures have substantial information beyond the existing ratings on Glassdoor, including the overall rating often examined in previous studies. Importantly, my text-based approach offers greater interpretability than the existing numerical ratings and provides more flexibility in what ESG aspects to capture as well. This way, my paper adds to the literature that uses text to capture hard-to-measure constructs in economics, such as product differentiation (Hoberg and Phillips (2016)), political risk (Hassan et al. (2019)), climate change exposure (e.g., Sautner et al. (2023)), and biodiversity risk (Giglio et al. (2023)). By studying employees' views, I also add to the literature that uses large-sale surveys to study people's attitudes on a wide range of economic issues, from environmental issues (e.g., Dechezleprêtre et al. (2022)), to social issues (e.g., Hvidberg, Kreiner, and Stantcheva (2023)), and corporate practices (e.g., Lee et al. (2021)).

Finally, this paper contributes to the literature on corporate cheap talk. Guiso, Sapienza, and Zingales (2015) show that the values that firms publicly advertise are uncorrelated with firms' financial performance. On greenwashing specifically, Raghunandan and Rajgopal (2021) show that Business Roundtable firms committed more E&S violations than other firms, while Bebchuk and Tallarita (2022) and Bebchuk, Kastiel, and Tallarita (2023) argue that corporations in general have done little in stakeholders' interests. Li and Wu (2020) show that public firms that join the UN Global Compact do not see declines in their negative ESG incidents. Baker et al. (2023) find that firms that often discuss diversity, equity, and inclusion are more likely to incur discrimination violations. While these studies rely on publicly disclosed information to assess firms' ESG practices, my paper relies on employee reviews, which I show to be robust to greenwashing. By focusing on what employees say about a firm's ESG practices, my approach also differs from simply including employee satisfaction as an indicator of ESG performance, as in Chava, Du, and Malakar (2021) and Heath et al. (2023).

2. Hypothesis development

In this section, I draw from the existing literature to form the hypotheses on whether employees can provide useful information about firms' ESG practices.

2.1. Do employees have ESG information beyond the existing ESG ratings?

Whether employees provide information about firms' ESG practices in their reviews depends on whether they care about these issues. Krueger, Metzger, and Wu (2023) find that Swedish employees accept lower wages to work for ESG-friendly companies, suggesting that employees have a preference for ESG practices. Even without a direct preference for ESG practices, employees may still care about some specific ESG issue because it is relevant for their well-being. Bonelli, Brière, and Derrien (2022) find that French employees reallocate away from their companies' stock when their companies have controversies on social issues (like working conditions), but not environmental or governance issues. Thus, I hypothesize that employees do care about ESG issues, but more so on the social category. However, that may not be the case in the US where ESG preference is less pronounced. Prior research has shown that ESG investing is more prevalent in Europe (Matos (2020)) and ESG investors in the US do not invest more in ESG-friendly firms (Gibson Brandon et al. (2022)).

Even when employees do care about ESG practices, they may not have information beyond the existing ESG ratings if they do not observe these practices firsthand. This possibility is more likely for the E category, as a firm's employees may not see its emissions or pollution in locations where they do not work. Thus, employees may not know about a firm's environmental performance beyond what the firm discloses to the public and ESG rating agencies. For the S category, however, it may be the opposite, because employees directly observe many social practices, like employee treatment and workforce diversity. For the G category, employees also observe many issues, such as compliance, business ethics, and leadership. In addition, prior research has shown that employees do know a lot about a firm's future financial performance (Sheng (2022)), which is a concept closer to G practices than E or S practices. Thus, if employees do care about ESG practices, they likely have more information on S&G relative to E issues.

Overall, it is an empirical question whether employees have information about ESG practices beyond the existing ESG ratings, and the answer may depend on the specific ESG category. Formally stated, the hypothesis I test is as follows, in its null form:

***H1**: The inside view does not add significant information to the existing ratings in predicting future indicators of ESG performance.*

2.2. Do employees have ESG information that is robust to corporate greenwashing?

Companies have an incentive to appear ESG-friendly given the recent trend in sustainable investing. Globally, 36% of all professionally managed assets was invested by some ESG criteria in 2020 (see https://www.gsi-alliance.org/). The sustainable investing industry has become so large that, globally, over 600 agencies were rating firms on ESG issues in 2018 (Wong, Brackley, and Petoy (2019)), creating an even more direct incentive for firms to appear more ESG-friendly.

Given such an incentive, existing ESG ratings likely suffer from a greenwashing bias, especially when most ESG ratings rely on data sources that firms can influence, such as corporate ESG reports, annual reports, and news (Douglas, Van Holt, and Whelan (2017)). For example, firms can inflate ratings by emphasizing immaterial ESG practices like charity donations, while neglecting costlier practices, such as diversity. Worse yet, ESG rating agencies often involve the rated firm in the rating process, further enabling the firm to influence its ratings. For instance, Dow Jones Sustainability Index provides companies with "feedback to help them improve and enhance their score and performance."[6] Empirically, Cornaggia and Cornaggia (2023) document the existence of ESG ratings management, while Tang, Yan, and Yao (2022) find that such practice is more likely when the rated firm shares common ownership with the rating agency.

The corporate greenwashing bias, however, is less likely to affect employees' inside view of ESG practices. A firm's employees have little incentive to greenwash its ESG image, especially under anonymity. Anonymous employees could share sensitive information, such as harassment or frauds without fear of retaliation. Campbell and Shang (2021) show that employee reviews predict corporate misconduct.

However, employees' information may still be affected by a corporate greenwashing bias. First, employees may paint a rosy picture of a firm as doing so could promote the firm's success, which is linked to job security for low-ranked employees and career prospects for high-ranked employees. Second, firms may try to manipulate their online reviews to appear more positive (Mayzlin, Dover, and Chevalier (2014), Gong and Thomas (2023)). This may apply particularly to Glassdoor as firms have been shown to take Glassdoor ratings seriously (Dube and Zhu (2021)). Nonetheless, Glassdoor's business model, which

[6] See https://corpgov.law.harvard.edu/2017/07/27/esg-reports-and-ratings-what-they-are-why-they-matter/.

hinges on being a trustworthy review platform, might mitigate this risk. The platform's give-to-get policy, for example, helps reduce extreme reviews, as Marinescu et al. (2021) show.

Overall, it is an empirical question whether employees' ESG information is affected by a corporate greenwashing bias (ESG cheap talk). To test this hypothesis, I will compare settings where firms make a costly vs. a costless commitment to ESG practices. If the inside view is robust to cheap talk, it should improve only after a costly ESG commitment. Formally stated, I test:

***H2**: The inside view is more likely to improve after a costly ESG commitment than after a costless ESG commitment.*

3. Data, measurements, and descriptive statistics

3.1. Data

I obtain employee reviews from Glassdoor.com. Glassdoor was launched in 2008, aiming to collect anonymous reviews from employees about employers. Glassdoor quickly became so popular that it started to provide job search services as well and became the number 2 job search site by user base in 2017. Glassdoor claims to review every contribution by its users to control quality.

I collect 10.4 million Glassdoor reviews for over 300,000 employers as of May 2021. A typical Glassdoor review contains a review title, date written, employee title, employee status (former vs. current), city and state of location, years in the company, numerical ratings for overall, work-life balance, culture, compensation, and management, and text fields containing the pros and the cons of working at the company. The Internet Appendix IA3 shows an example.

To capture an outside view of firms' ESG practices, I collect the MSCI (formerly KLD) ESG ratings, which have been used extensively in the ESG literature. MSCI employs over 100 analysts to annually rate companies on ESG issues. For each issue, the analysts record a firm's strengths and weaknesses on that issue. I take the number of strengths relative to weaknesses, and scale it by the sum of both, to be my main MSCI ESG ratings (Gao, He, and Wu (2021)).

I also collect firms' violations with regulatory agencies from the Violation Tracker database. The database covers over 400,000 violation records between 2000 and 2020, totaling over $600 billion in penalties. It sorts violations into nine groups: environment, consumer protection, employment, healthcare, competition, financial, government contracting, miscellaneous, and safety-related offenses, allowing me to group them into E, S, and G categories.

Finally, I collect firms' internal control weaknesses from Audit Analytics, stock returns from CRSP, accounting data from Compustat, mergers from SDC Platinum, institutional ownership from WRDS Thomson Reuters Stock Ownership, COVID exposure from Koren and Peto (2020), the list of cyber-attacks from Kamiya et al. (2021), among others.

To construct my sample, I start with 7,851 US companies having 100 or more Glassdoor reviews as of July 2020. I match these firms to Compustat data during 2008-2020 using stock tickers and company names to arrive at my main sample of 1,936 public firms. My sample is larger than those in other studies using Glassdoor data, such as Green et al. (2019) with 1,238 firms.[7] My sample's industry composition (Internet Appendix Table IA1) appears similar to that of similarly sized Compustat firms in the same period, except that my sample has more business services and retail firms and fewer banking and pharmaceutical firms, similar to Green et al. (2019).

I then merge my sample with the MSCI ESG ratings and the Violation Tracker data, as detailed in the Internet Appendix IA1. Before merging, I aggregate the violation data to the parent firm-year level. I impute the violation count and the penalty amount as zero when they are missing.

The final sample is a panel of 27,104 firm-years between 2008, Glassdoor inception year, and 2021, with 12,360 non-missing observations for the MSCI ESG ratings and 22,186 non-missing observations for the Glassdoor reviews data. This sample covers 2,444,040 Glassdoor reviews in total. Table 1 shows the summary statistics for the main variables.

3.2. Measuring an inside view of ESG practices

To measure employees' inside view of ESG practices, I identify the words that employees often use to describe ESG issues. First, I construct seed word lists for E, S, and G topics based on how academics and industry experts view these topics. Next, to ensure that my final dictionaries of ESG words are comprehensive and specific to the language of employee reviews, I employ a word-embedding technique to identify from the universe of employee reviews the words that are most similar to my seed words. Once I have the comprehensive dictionaries of ESG words, I capture the employees' inside view of ESG practices

[7] Green et al. (2019) uses a cutoff of minimum 15 reviews per quarter for their sample. When I use a similar cutoff, my sample still has above 1,600 firms, likely because firms tend to have more reviews as Glassdoor user base grows.

by how often the employees mention these words in their reviews' pros relative to cons sections. The following subsections describe these steps in detail.

3.2.1. Preparing the seed word lists for ESG topics.

To prepare the seed word lists for ESG topics, I first collect clearly defined lists of E, S, and G issues from various sources. From industry experts, I rely on ESG rating agencies, whose methodology documents often include a list of ESG issues. I focus on the five major rating agencies studied in Berg, Koelbel, and Rigobon (2022), namely MSCI, Refinitiv, RobecoSAM, Sustainalytics, and Vigeo-Eiris. I then add RepRisk for its aggregation of negative ESG news and CSRHub for its attempt to synthesize ESG issues from many rating agencies. Less well-known agencies rarely publicize their proprietary rating methodology. From academic experts, I find few papers that clearly specify lists of E, S, or G issues: Bessec and Fouquau (2021) with a list of E issues from dictionaries like the EPA's glossary and Baier, Berninger, and Kiesel (2020) with 300 ESG words collected from the annual reports of America's 25 biggest firms. Overall, I obtain 37 lists of ESG issues, as shown in the Internet Appendix Table IA2.

Next, I identify the words (and phrases) that appear most often across the lists of issues for each ESG category. For each word, I rank it by its relative frequency, which is how often it appears in one category relative to others. Then, I find the top 25 words and the top 25 two-word phrases with the highest average relative frequency on each ESG category. This forms a list of 50 words that industry experts and academic papers often use on each ESG category (Table IA2 Panel B).[8]

3.2.2. Extending the ESG word lists using machine learning

To make my ESG word lists comprehensive and specific to the language of employee reviews, I follow Hanley and Hoberg (2019) and Li et al. (2021) to find the words that share similar meanings to my ESG seed words, by training *word2vec* (Mikolov et al. (2013)), a word-embedding model, on 10.4 million employee reviews. *Word2vec* is a two-layered neural network that takes a word as input and returns a predicted distribution of neighboring words. The middle layer of this network thus retains the model's knowledge of what words often surround the input word in a review. Thus, the middle layer can be used as

[8] I use a cutoff of 25 because beyond that, the relative frequency of many words starts to become the same, so ranking them becomes impossible. I adjust the raw frequency of each word by the tf.idf convention in textual analysis.

the vector representing the input word. I follow Li et al. (2021) to clean text data and train my *word2vec* model (detailed in the Internet Appendix IA4).

After training the *word2vec* model, I use it to refine my seed word lists. First, I calculate the average of the vectors representing the seed words in each ESG category to represent that category. This allows me to remove noisy seed words for any ESG category by removing words outside of the most similar words for that category.[9] In addition, I consider diversity issues as an S issue and thus remove diversity-related words from the G seed word list. I further remove several noisy words to arrive at the final seed word lists shown in Table 2 Panel A.[10] The refined seed word lists include meaningful ESG words, such as *biodiversity* and *carbon footprint* for E topics, *community* and *age discrimination* for S topics, and *corruption* and *day-to-day operation* for G topics.

After refining my seed word lists, I obtain the full dictionary on each ESG category by finding the 500 words with the highest similarity to the average vector representing that category, following Li et al. (2021). When a word appears in multiple categories, I keep it only in the category to which it is most similar, as in Li et al. (2021), so the final ESG dictionaries have only 1,382 unique words in total. Table 2 Panel B shows that these steps add meaningful words, such as *biofuel* and *fertilizer* on E topics, *advocacy* and *social justice* on S topics, and *malfeasance* and *embezzlement* on G topics. The Internet Appendix Table IA3 includes the full ESG dictionaries.

For robustness, the semi-final panel in the Internet Appendix Table IA3 shows how the final dictionary would look like with different cutoffs for the dictionary's size. It shows that even when each dictionary extends to 1000 words, most, if not all, of the added words have meanings that are tightly related to ESG topics, such as *pollute* and *hazardous* for the E category, *donation-charity* and *watchdog* for the S category, and *inner working* and *nonperformance* for the G category.

This step of extending the ESG word lists is important. Without it, I find in un-tabulated analyses that my resulting ESG measures become less predictive of future ESG-related outcomes.

[9] In particular, I remove words outside of the 1000 words with the highest cosine similarity with the category's average vector. Changing the cutoff from 1000 to 500 does not change the final seed word lists substantially (by under 7%).

[10] Specifically, I remove *supply chain* from the E category's seed words because even when I include it, the resulting extended dictionary (500 words) does not include it. I also remove *fundamental* from the S category, and *financial institution* and *government agency* from the G category.

3.2.3. *Scoring firms by counting ESG words*

After generating the full ESG dictionaries, I measure the inside view at the review level for each ESG category separately. This is done for each review by calculating the percentage of words in the pros section that fall into each category, net of the percentage of words in the cons section that belong to the same category. Averaging this measure across reviews in a firm-year creates my main measure of the inside view. I winsorize the measure at the 1st and 99th percentiles to reduce the effect of outliers.

My approach in measuring the inside view of ESG practices is novel. First, it distinguishes between positive and negative views of ESG practices. Previous studies, by contrast, do not. For example, Li et al. (2021) count words on culture topics in a firm's earnings calls to measure corporate culture, regardless of whether these words are mentioned in a positive or negative context. Second, my approach exploits the unique feature that each Glassdoor review contains a pros section and a cons section, so there is no need for supervised learning or sentiment analysis. Of course, some employees may mention a pro-ESG practice in the cons section, creating noise in my measure. I find that such cases are very rare (see Section 6).

3.3. *How does the inside view look like?*

In this section, I examine some descriptive statistics of the employees' inside view to see whether it appears useful in capturing ESG practices. First, I examine how much attention employees pay to ESG issues. The inside view can only be useful if employees pay significant attention to ESG issues. Second, I examine whether ranking firms based on the inside view appears sensible.

3.3.1. *Employees' attention to ESG issues*

I find that employees pay substantial attention to ESG issues, but more so on S and G topics than on E topics. Table 1 Panel B shows that 43% of reviews mention at least a word from the ESG dictionaries developed in Section 3.2. Specifically, 28% of reviews mention at least a word on the G category and 22% of reviews mention at least a word on the S category while 2% of reviews mention some E key word. The results are remarkably stable, as it appears very similar in the full sample of 10.4 million reviews, which include reviews on both public and private firms, as shown in Table 1 Panel C. Even with the smaller list of ESG words using a 250-word cutoff per ESG category, over 34% of reviews mention some ESG word.

Moreover, while the frequency of ESG catchphrases like *ESG*, *CSR*, and *sustainability* in reviews has increased substantially between 2008 and 2021, the employees' attention to a broader set of ESG topics, as measured by the frequency of words from my full ESG dictionaries, has remained stable over time, suggesting that the employees have cared about ESG issues throughout the period. The employees' attention, nonetheless, spiked around major ESG-related events, such as the Paris Agreement, the COVID Crisis, and the death of George Floyd. The Internet Appendix IA5 provides further detail on employees' aggregate attention to ESG issues over time.

3.3.2. Top and bottom firms by the inside view

In this section, I examine the firms with the highest and lowest inside view on each ESG category. Table 3 Panel A shows the top 5 firms and bottom 5 firms based on their average inside view between 2014 and 2018 for each ESG category, among the largest 500 firms by average total assets. Table 3 Panel B shows excerpts from two actual reviews of the top and bottom firms.

Based on the inside view, SunEdison Inc., a solar energy firm, ranked top on the E category, while Pioneer Natural Resources, a coal producer, ranked bottom. Select reviews indicate that SunEdison was accelerating in the solar energy sector with excellent energy storage technology while expanding into wind energy. Even an employee who rated SunEdison one star overall acknowledged the firm's potential to address global energy shortage. Select reviews from Pioneer Natural Resources, by contrast, highlighted the firm's poor management of oil fields and its "shifting focus to horizontal drilling", which is known to have impact the environment more than vertical drilling. Another employee states that Pioneer could "do more core analysis and research."

Based on the employees' inside view of S practices, Umpqua Bank, a community bank, ranked top, while Pepco Holdings, a large electric utility firm, ranked bottom. Select reviews from Umpqua Bank indicated that the bank "listened to employees" and promoted "community involvement." In particular, employees praised the bank for providing 40 hours of paid volunteering annually. Employees from Pepco Holdings, however, complained about the lack of gender equality and poor work-life balance with "too many hours required to be worked."

As for governance, LinkedIn, the company behind the world's largest professional network, ranked first, while Sterling Bancorp ranked last. Select reviews from LinkedIn indicated that the firm had "outstanding leadership" and "culture and values" that were "felt throughout the organizations." Reviews from Sterling Bancorp, by contrast, indicated that the firm was "very disorganized" and had "too much pressure for sales", implying weak internal controls and overly aggressive performance incentives.

4. Is the inside view informative beyond the existing ESG ratings?

In this section, I examine how informative the inside view is in predicting future ESG performance indicators across firms, relative to the ESG ratings by MSCI, the largest ESG rating provider by revenue (Berg et al. (2023)). The focus on prediction is because ESG assessments are useful if they are forward-looking (Edmans (2023)). Moreover, focusing on predictions helps rule out the possibility that employees' inside view merely reflects public signals of a firm's current or past ESG performance.

On each ESG category, I study ESG performance indicators that are relatively harder for firms to manipulate. With each indicator, I regress its value in year t+1, t+2, or t+3 on the inside view of the same ESG category in year t, while controlling for industry fixed effects, year fixed effects, firm size, and operating performance (ROA), also in year t, as in Li et al. (2021).[11] In addition, I control for Glassdoor' overall rating, a numerical rating employees provide on the website, as prior research has shown that this measure of overall employee satisfaction is informative about a firm's future performance. [12]

Finally, I explore whether the ESG inside view measures are significantly associated with a firm's future financial performance, as captured by its valuation ratio, downside risk, and stock returns.

4.1. Predicting environmental performance indicators

It is difficult to find environmental (E) performance indicators that are not prone to corporate greenwashing because data like carbon emissions come from firms' own disclosure. However, within a firm's disclosed indicators, there are two indicators that are relatively harder to greenwash. The first indicator is the total emissions of a firm, including its Scope 3 emissions, or emissions that occur within the firm's supply chain, beyond its direct operations (Scope 1 and 2 emissions), making Scope 3 emissions harder to manipulate. In contrast, firms might manipulate Scope 1 or Scope 2 emissions by offloading pollutive assets to suppliers, a strategy noted by Duchin, Gao, and Xu (2022). The second indicator is whether a firm reports its Scope

[11] Unlike Li et al. 2021, I use the Fama French (FF) 48-industry instead of the FF 12-industry classification as ESG practices may vary a lot across specific industries. The results are similar with the 12-industry classification.

[12] Controlling for the overall rating also rules out the reverse causality concern that firms whose employees are optimistic about future prospects (including ESG outcomes) may have a higher inside view, as the overall rating should capture such employee optimism.

3 emissions, as the act of disclosing these emissions has been identified as an indicator of environmental stewardship and has been linked to substantial emission reductions throughout the supply chain, according to Cho et al. (2024). I collect firms' disclosed emissions from Refinitiv's Asset4 database.

Table 4 shows the results. Panel A column (1) suggests that a one standard deviation higher in the E inside view is associated with 7.25% (exp(0.07)-1) higher in the likelihood of a firm disclosing Scope 3 emissions one year ahead. This estimate is significant at the 5% level and remains so after controlling for the MSCI E rating in column (2), as well as industry fixed effects, year fixed effects, and a firm's current size and operating performance. The estimate becomes even more significant (at the 1% level) and larger in magnitude (over 9%) after controlling for a firm's overall rating on Glassdoor (column 3). The inside view significantly predicts the likelihood of a firm's disclosing Scope 3 emissions in two and three years ahead as well, with similar statistical and economic significance (columns 4 to 9).[13]

Table 4 Panel B shows that the inside view has even better predictive power for a firm's total emissions. While the MSCI E rating shows no significant power in predicting a firm's total emissions (in logarithm), the E inside view does.[14] A one standard deviation higher in the inside view is associated with between 1.5% and 1.9% lower in a firm's total emissions one year ahead, after many controls, including the MSCI E rating (columns 1 to 3). This estimate is statistically significant at the 1% level. It remains similarly significant in the two or three year ahead predictions (columns 4 to 9).

In un-tabulated tests, I find that the results are highly robust. They remain similar after controlling additionally for a firm's governance structures, such as its entrenchment index (Bebchuk, Cohen, and Ferrell (2009), and institutional ownership, which Dyck et al. (2019) show to matter for firms' ESG practices. The results also hold after controlling for more firm-level characteristics, including sales growth, cash ratio, debt ratio, and valuation (Tobin's Q). Using a broader industry classification or controlling for industry times year fixed effects do not change the results either. Finally, the E inside view still has significant predictive power even after controlling for all the numerical ratings on Glassdoor beyond the

[13] The E inside view also predicts a firm's likelihood of disclosing Scope 1 or Scope 2 emissions, but with less statistical significance than predicting Scope 3 disclosure, while the MSCI E rating more significantly predicts the disclosure of Scope 1 or 2 emissions, suggesting that the inside view is less affected by more greenwash-able metrics.

[14] Taking the logarithm of total emissions is necessary to make the dependent variable have a distribution closer to a normal distribution and thus more suited to the assumptions underlying OLS regressions.

overall rating, including the ratings of culture, work-life balance, senior management, career prospect, and compensation.[15]

I also study other E indicators that are relatively easier to greenwash. One indicator is a firm's emission intensity, which is the ratio of its emissions to its sales. This indicator is easier to greenwash than the level of emissions, as scaling by sales will make companies with a lot of revenue like oil and gas conglomerates to look more environmentally friendly. Bolton and Kacperczyk (2021) show that investors appear to price a firm's carbon risk, but only according to its level of carbon emissions, but not its emissions intensity. Another indicator is whether a firm has a settled penalty with a regulatory agency like the EPA (Environmental Protection Agency) in a year. Settlement of any environmental violation, however, could take years from the moment when the actual violation happens, and may not materialize if a firm has good lawyers. For these indicators, I find in un-tabulated analyses that the E inside view does not have significant predictive power while the MSCI E rating has, suggesting that employees' inside view is less correlated with greenwash-able metrics than the MSCI rating.

Overall, the inside view has significant information beyond the MSCI rating on the E category, especially on environmental dimensions that are harder for a firm to greenwash.

4.2. Predicting social performance indicators

Finding social performance indicators that are less prone to greenwashing (ESG cheap talks) is also hard. Luckily, there are some limited indicators that are independently created and externally verified about firms' social performance. One is an indicator of whether a firm is in the Best 100 Companies to Work For, a list that the Great Place to Work Institute constructs from an anonymous survey of companies' employees. I collect this indicator from the website of Alex Edmans, who has verified the informativeness of this indicator in many papers (e.g., Edmans (2012)). Another indicator is whether a firm is in the Best Companies for Diversity list, which Fortune Magazine constructs based on survey responses from minority workers, such as women, LGBTQ employees, and people of colors.

Table 5 shows the results. Panel A Column (1) indicates that a one standard deviation higher in the S inside view is associated with 73% higher in the odds of a firm landing on the Best Companies to Work For

[15] I do not control for an environmental (E) indicator's lagged value, as a firm's E performance is highly persistent (e.g., an autocorrelation of 0.98 for log total emissions, and 0.74 for Scope 3 disclosure). Un-tabulated tests show that the E inside view still has significant power in predicting Scope 3 emissions disclosure in year t+1.

list one year ahead. This estimate is statistically significant at the 1% level after controlling for industry fixed effects, year fixed effects, firm size, and operating performance, as well as the MSCI S rating (column 2) and the Glassdoor overall rating (column 3). The predictive power is similarly large and significant over the two or three years ahead (columns 4 to 9). In un-tabulated tests, I find that the inside view's ability to predict the Best Companies list continues to hold after controlling for institutional ownership (Dyck et al. (2019)), entrenchment index (Bebchuk, Cohen, and Ferrell (2009)), industry times year fixed effects, more firm level controls (cash, debt, and Tobin's Q…), whether a firm has been on the Best Companies list before, as well as all the numerical ratings on Glassdoor.

Table 5 Panel B shows that the S inside view predicts a firm's future likelihood of joining the Best Diversity list even better. Panel B columns (2) (5) and (8) show that the coefficient on the MSCI S rating is not statistically significant at any conventional levels while the coefficient on the S inside view is, at the 1% level. The magnitude is large, across all the prediction horizons. For example, a one standard deviation higher in the S inside view is associated with a 2.5 times higher (exp(0.93)) in the odds ratio of a firm landing on the Best Diversity list in one year ahead. The inside view's ability to predict the Best Diversity list is highly robust. In un-tabulated tests, it holds strongly even after controlling for a firm's governance structures, valuation, cash, and debt, different industry classifications, industry times year fixed effects, as well as all the numerical ratings on Glassdoor, and a lagged indicator of whether the firm has been on the list before.

I also study firms' violation records related to social issues, such as discrimination-related penalties charged by regulatory agencies, from the Violation Tracker database. Since the database collects firms' violation at the time of the penalty's settlement, each violation record does not have a clear timing of when the actual violation happened. In addition, it is hard to prove social misconduct like discrimination and firms may be able to avoid publicly visible settlements via private negotiations. Therefore, I caution against using a firm's future violation penalties as a validator for ESG measures. Nonetheless, in un-tabulated analyses, I find that both the MSCI S rating and the S inside view are significantly and negatively associated with a firm's future number of social violation records and the associated penalty relative to sales.

4.3. Predicting governance quality indicators

Again, I focus on indicators that are relatively harder for firms to manipulate, on governance topics. First, I examine a firm's number of internal control weaknesses, which are reported by a firm's external auditor every year, as required by the Sarbanes-Oxley Act of 2002. I collect this data from Audit Analytics. Second, I examine a firm's misstatement risk, or the probability of the firm's having a material accounting error, which the SEC requires all firms to disclose in their Forms 8-K. Instead of using the actual reporting of the error, which has a different timing from when the error actually happened, I follow Bertomeu et al. (2021) to infer a firm's misstatement risk in a given year from its accounting numbers and market conditions in that year using a machine learning model. I obtain the data on misstatement risk from Bertomeu et al. (2021)'s website.[16]

Finally, I study the number of Forms 13D filed by a firm's activist shareholders as an indicator of poor governance. A shareholder activist is required to file such a form when the activist acquires over 5% ownership of a firm with an intent to alter the firm's policies. So, many Forms 13D mean that a firm's large shareholders want its policies to change, a sign of poor governance. Edmans (2009) argues that such large shareholders are more likely to research the firm more deeply, so their dissatisfaction with the firm is likely to be an informative indicator of its governance quality.

Table 6 reports the results on how the governance (G) inside view predict these governance quality indicators in the future. Panel A column (1) shows that a standard deviation higher in the G inside view is associated with 0.39 higher in a firm's number of internal control weaknesses one year ahead. This estimate is large, equivalent to 2.6 times the sample mean of the number of internal control weaknesses. It is significant at the 1% level and remains so after controlling for the MSCI governance (G) rating, Glassdoor overall rating, as well as industry fixed effects, year fixed effects, and firm size and operating performance (columns 2 and 3). The inside view's predictive power is also large and highly significant in predicting the number of internal control weaknesses in two or three years ahead (columns 4 to 9). By contrast, the MSCI G rating shows a poor ability to predict this governance indicator. The coefficient on the MSCI rating is

[16] Other indicators of governance quality related to accounting issues include SEC enforcement actions and accounting lawsuits. I do not study these indicators because their timing may be different from the timing of the actual misconduct. In addition, firms can avoid lawsuits and enforcement actions by lobbying and having good lawyers.

either insignificant across some columns, or has the wrong sign in some columns (5 and 6). Moffitt, Patin, and Watson (2023) also find that the MSCI G rating does not predict internal control weaknesses.

Table 6 Panel B shows the results about predicting a firm's misstatement risk. The G inside view is negatively and significantly associated with a firm's lower misstatement risk in one, two, or three years ahead (column 1, 4, and 7). It remains so after controlling for the MSCI G rating (columns 2, 5, and 8), the Glassdoor overall rating (columns 6 and 9), as well as industry fixed effects, year fixed effects, and firm size and operating performance. By contrast, the MSCI G rating exhibits no significant relationship with future misstatement risk across all the columns. [17]

Table 6 Panel C shows the results about predicting the number of activism events by large shareholders (Forms 13D). A one standard deviation higher in the G inside view is associated with between 0.11 to 0.14 lower in the number of activism events, in one, two, or three years ahead (columns 1, 4, and 7). This estimate is significant at the 1% level, and economically large: above 100% relative to the sample mean (.104). It remains significant and large after controlling for the MSCI G rating and the Glassdoor overall rating, but only for the prediction over the three years ahead (columns 8 and 9), suggesting that employees often know useful information about a firm's governance issues many years ahead before shareholder activists take actions. By contrast, the MSCI G rating shows insignificant predictive power across all the regressions.

In un-tabulated tests, I find that the inside view's ability to predict the governance quality indicators above is highly robust. The results are either the same or even stronger after controlling additionally for a firm's institutional ownership, entrenchment index, and many more firm characteristics like cash ratio, debt ratio, sales growth, and valuation. The results remain significant after controlling for industry fixed effects by a broader industry classification, industry times year fixed effects, all the numerical ratings on Glassdoor, and the lagged dependent variable in each predictive test. Thus, reverse causality and omitted variables related to industry trends, firms' financial resources, and employee satisfaction (or the halo effect) are unlikely to drive the results.[18]

Overall, the findings suggest that the employees have substantial information about firms' governance quality that the MSCI governance rating does not have.

[17] The results hold after controlling for all numerical ratings on Glassdoor, so they distinct from prior research, such as Ji, Rozenbaum, and Welch (2017), who show that Glassdoor culture rating predicts future accounting issues.

[18] Reverse causality is unlikely also because, in un-tabulated tests, the inside view still predicts future outcomes after I instrument the inside view by its past values up to a 5-year lag, as similarly done in Gu and Hackbarth (2021).

4.4. Predicting firms' financial performance

In this section, I investigate whether the employees' inside view on ESG practices has information about firms' future financial performance beyond the MSCI ESG ratings. I perform tests similar to the previous sections, but focus on predicting firms' future valuation, downside risk, and stock return. I capture valuation by Tobin's Q, the ratio of a firm's market value of assets to its book value of assets, following Aggarwal et al. (2009). I capture downside risk using the two measures used in Hoepner et al. (2020). The first is downside volatility, or the standard deviation of daily returns that are negative during a year. The second is tail risk, or the average absolute value of the lowest 5% of daily returns during a year. I measure a firm's stock return in a year by the buy-and-hold stock return from January 1st to December 31st in that year.

Table 7 shows the results. Panel A column (1) indicates that a higher inside view is associated with a higher valuation ratio (Tobin's Q) one year ahead, but only on the S and G category, not the E category. The economic magnitude is larger for the G category, implying a 14% standard deviation higher in Tobin's Q per one standard deviation higher in the G inside view. These effects are significant at the 1% level after controlling for a firm's past operating performance, size, industry, and year fixed effects. They remain similar after controlling for the MSCI ESG ratings (column 2). After controlling for the Glassdoor overall rating (column 3), the G inside view remains significantly associated with future valuation while the S inside view does not, suggesting that the S inside view matters for valuation because it is associated with employee satisfaction, which prior research has shown to be positively linked to firm value (e.g., Edmans (2011)).

The MSCI ESG ratings are also significantly associated with a firm's future valuation. However, they do not make economic sense for the G category, as it appears that a higher MSCI G rating is associated with a lower valuation, contradicting prior research that better corporate governance is associated with higher firm value, both theoretically (e.g., Jensen and Meckling (1976)) and empirically (e.g., Gompers, Ishii, and Metrick (2003)). The results are similar for predicting valuation in two or three years ahead (columns 4 to 9). Overall, the inside view predicts future valuation better than the MSCI ESG ratings.

Panel B focuses on predicting a firm's downside risk. It shows that a higher inside view is associated with a lower downside risk for a firm in the future, but only on the G category. The association is statistically significant at the 1% level across all the prediction horizons (columns 1, 4, and 7), and remains so after controlling the MSCI ESG ratings (columns 2, 5, and 8). After controlling for the Glassdoor overall rating, the G inside view is still significantly associated with future downside risk, at the 1% level, in two or three years ahead (columns 6 and 9). By contrast, the MSCI ESG ratings do not predict future downside risk consistently across different horizons, sometimes significant for the S category, but sometimes significant for the G category, and at most at the 5% significance level. The results are similar with the other measure of downside risk. Overall, the inside view outperforms the MSCI ESG ratings in predicting future downside risk.

Panel C focuses on predicting a firm's future stock returns. Column (1) indicates that the inside view is positively associated with a firm's stock return in one year ahead, but only on the G category (i.e., no effect on the E or S category). This relationship is statistically significant at the 1% level after controlling for a firm's past operating performance and size, as well as industry and year fixed effects, and continues to be significant at the 5% level after controlling for all the MSCI ESG ratings (column 2). Even after controlling additionally for the Glassdoor overall rating, it remains significant at the 10% level (column 3). The prediction over the two or three years ahead is also significant, with more statistical significance (up to the 1% level) in the two year ahead prediction regardless of the control variables (columns 4 to 6). The MSCI ESG ratings also have some significant power in predicting future stock returns, but only on the S category, and with lower statistical significance (up to the 5% level).

In un-tabulated analyses, I find that the inside view's ability to predict the financial outcomes above is highly robust. It remains similar after controlling additionally for a firm's governance structure (institutional ownership or entrenchment index), industry times year fixed effects, more firm-level controls (e.g., cash and debt ratio, research and development (R&D) over assets, …), and all the numerical ratings on Glassdoor, suggesting that omitted factors related to corporate governance, industry trend, and the halo effect are unlikely to drive the results. In addition, the inside view still significantly predicts future financial outcomes when I control for these outcomes' lagged values, suggesting that employees have information that market participants do not know yet. Overall, the employees' ESG inside view has significant information about firms' financial performance beyond the existing ESG ratings and many predictors known to the literature.

5. Is the inside view robust to greenwashing?

In this section, I evaluate whether the employees' inside view is robust to greenwashing, i.e., ESG cheap talk. I do so by comparing low-cost and high-cost commitments that firms make about improving their ESG practices. If the inside view is robust to ESG cheap talk, it should not improve after a low-cost commitment, but it should improve after a high-cost commitment, as a costly commitment is a more credible signal (e.g., Spence (1973), Riley (1979)). Finally, I examine how the inside view changes after an ESG-specific exogenous shock, which raises some firms' cost of poor ESG practices while leaving others intact.

5.1. When CEOs subscribe to the Business Roundtable's stakeholder view

In August 2019, nearly 200 chief executive officers (CEOs) signed the new "Statement on the Purpose of a Corporation" by Business Roundtable (BRT), an association of CEOs in America's largest companies. The new statement emphasizes "a fundamental commitment to all stakeholders", which differs from the old statement since 1997 that "corporations exist principally to serve shareholders".[19]

The prior literature argues that the BRT statement is likely cheap talk. Bebchuk and Tallarita (2020) document that most firms did not seek board approval in signing the BRT letter and Raghunandan and Rajgopal (2021) show that these firms had poor records of ESG practices. After signing the letter, these firms have had little change in their bylaws and compensation schemes to advance stakeholders' interests (Bebchuk and Tallarita (2022)). If employees' information is not affected by cheap talk, it should not improve after the BRT commitment.

To test this hypothesis, I regress the change in the inside view from 2018 to 2020 on a BRT indicator and firm characteristics. I collect the list of BRT firms from the BRT website. Among these firms, I find stock identifiers for 183 firms with 143 successful matches to my main sample.[20]

Table 8 Panel A shows that signing the BRT statement is not associated with any significant change in the inside view. The coefficient on the *BRT* indicator is statistically indistinguishable from zero in columns (1) to (3). In columns (4) to (6), I allow the coefficient on *BRT* to vary with indicators of high or low institutional ownership, analyst coverage, organizational complexity, advertising intensity, or COVID

[19] https://opportunity.businessroundtable.org/ourcommitment/.

[20] I cannot analyze how the MSCI ESG ratings changed after the BRT commitment because MSCI discontinued their KLD ESG ratings in 2019 to start a brand-new set of ESG ratings.

exposure (Koren and Peto (2020)). The only statistically significant result is that BRT firms with a high organizational complexity saw a larger decline in the inside view of environmental practices relative to other firms. Table 8 Panel B shows that even when I split the sample by above- or below-median prior inside view, the coefficient on *BRT* continues to be statistically indistinguishable from zero across columns. In un-tabulated tests, I find that the BRT firms did not have a better inside view than other firms before 2019 either. The results remain unchanged when I use propensity score matching to find control firms for each BRT firm based characteristics measured in 2018, as in Raghunandan and Rajgopal (2021). Overall, the results imply that employees do not view the BRT statement as a credible ESG commitment.

5.2. When firms commit to the United Nations Global Compact

The United Nations Global Compact (UNGC) claims itself to be the world's largest corporate sustainability initiative. Its goal is to support companies to align themselves with ten principles across dimensions like human rights and anti-corruption. Between 2000 and 2020, more than 22,000 companies have joined the UNGC, thus explicitly stating a commitment to ESG practices. In this section, I investigate whether this commitment is credible.

Unlike the BRT commitment, the UNGC commitment requires board approval. In addition, the UNGC has publicly expelled over 40% of its participants for failure to communicate progress, implying a high reputational cost of the commitment. Thus, a firm might be more likely to improve its ESG practices after joining the UNGC than otherwise similar firms.

I obtain the list of all firms that have ever joined the UNGC from the UNGC website. Of over 29,000 organizations worldwide that have ever joined the UNGC by 2021, over 22,000 are companies. Of these firms, 965 are domiciled in the US. I manually narrow this list to 203 US public firms with a valid CUSIP identifier. After matching with Glassdoor and Compustat, I arrive at a sample of 162 UNGC firms.

I conduct propensity score matching to identify appropriate control firms for each firm that ever joined the UNGC, by using a logit model based on firm characteristics (size, ROA, leverage, sales growth, Tobin's Q, and institutional ownership) and lagged ESG inside views.[21] I then match with replacement each UNGC firm in its first year of UNGC participation with up to 10 control firms using the propensity score within a caliper of 0.1 in the same year and industry. The caliper requirement ensures that only close-enough matches

[21] The lagged ESG inside views do not significantly predict the chance of a firm's joining the UNGC.

are selected, so in the end my sample includes 539 unique control firms for 111 UNGC firms that have the required data. These control firms have never joined the UNGC, so my research design avoids potential caveats with using already-treated firms as controls, as detailed in Goodman-Bacon (2021).

For each firm, I calculate the change in the average E, S, or G inside view from three years before to three years after the firm joins the UNGC. I then regress it on an indicator *UNGC* of whether a firm has joined the UNGC. Basically, I am running a diff-in-diff test by stacking together panels of treated and control firms around the treatment year, i.e., a stacked regression design recommended by Baker, Larcker, and Wang (2022), but collapsing the time series information into a pre-period and a post-period to reduce the chance of false discovery (Bertrand, Duflo, and Mullainathan (2004)) while making my test results more easily comparable to the BRT test results.

Table 9 Panel A shows the results. Without control variables, columns (1) to (3) indicate that UNGC firms improve their ESG inside view by 17% to 20% standard deviation more than control firms for the S and G categories with statistical significance at the 1% and 10% levels, respectively. After controlling for firm characteristics, the coefficients on the *UNGC* indicator becomes less statistically significant (at the 10% level in column (5)), but the economic magnitude remains significant: 11% and 17%. I also interact the *UNGC* indicator with indicators of whether a firm has high (above-sample-median) institutional ownership, analyst coverage, organizational complexity, or advertising intensity in columns (7) to (9). The only significant result is with institutional ownership. The corresponding coefficient is negative, implying that employees view governance to improve less in UNGC firms with high institutional ownership.

Table 9 Panel B shows the same results in high or low ESG inside views before a firm joins the UNGC (relative to sample median). The coefficient on *UNGC* is positive and significant at the 1% level in the sub-sample with a high prior S inside view (column 3) while it is positive and significant at the 10% level in the sub-sample with a low prior G inside view (column 6). These results are hard to explain if joining the UNGC is merely cheap talk.[22]

5.3. An exogenous shock to the incentives to walk the ESG talk.

If the inside view captures a firm's internal ESG practices well, it likely improves when the firm has a strong incentive to walk the ESG talk, such as when poor internal ESG practices become more costly. In

[22] In un-tabulated tests, I find that the MSCI ESG ratings improve for UNGC firms relative to other firms after joining the UNGC. The improvement is statistically significant on the E and G categories, and strongest on the joining year.

this section, I study such a shock regarding one important dimension of ESG practices: diversity and inclusion (D&I).[23]

In the United States, employers can be held liable for workplace harassment if the harasser has a supervisory role over the victim, under the Title VII of the Civil Rights Act of 1964. However, in July 2013, the 7th Circuit Court, which set precedents for legal cases in Illinois, Indiana, and Wisconsin, unexpectedly held an employer liable for sexual and racial harassment even when the harasser was merely a co-worker of the victim (*Lambert v. Peri Formworks Sys., Inc.*). Thus, the court ruling raised the risk of harassment lawsuits for firms located in those three states (treated firms) relative to firms located elsewhere (control firms). In addition, the Court ruled against the employer despite the employer's existing policies on handling harassment complaints, so the treated firms could not simply add more policies to circumvent the increased legal risk, and thus had a stronger incentive to *truly improve internal* diversity and inclusion (D&I) practices. Consequently, the treated firms were more likely to improve their inside view of social practices, which include D&I practices, after the court ruling.

I conduct a difference-in-differences test to study how the inside view changes around the 2013 D&I-related ruling for the treated firms relative to the control firms. Because employees mention social practices in under 25% of the reviews and D&I is only a subcategory of the social practices, I restrict the sample to firm-years with at least 10 reviews (25th percentile) to ensure that the inside view measure can capture meaningful changes in a firm's practices related to the court ruling.[24]

Table 10 Panel A shows the results. The coefficient on the *Treat*Post* interaction is positive and statistically significant at the 1% level for the social (S) category, but negative and statistically insignificant for the environmental (E) and governance (G) categories (columns (1), (4), and (7)), suggesting that the inside view improved after the court ruling only for the S category. When I break the *Post* indicator down to indicators for individual years since the court ruling, I find that the improvement in the S inside view was most pronounced in the year of the ruling and two years later (column (5)). While there is no significant

[23] By contrast, following a shock that increases a firm's incentive to *only* talk about ESG practices, actual ESG practices are unlikely to improve. I consider cyber-attacks as such shocks, as Akey et al. (2021) shows that a cyber-attack induces firms to improve their ESG image. I find that the ESG inside view hardly improves after a cyber-attack.

[24] Without this minimum-reviews restriction, the results are qualitatively similar, albeit with less statistical significance, as expected with noisier data. An alternative way for my measure to focus enough on the social practices most relevant to the court ruling is to capture an inside view of diversity and inclusion (D&I) directly. I do that in the Internet Appendix IA6 and find statistically significant results similar to my main findings.

result for the E category, the same test for the G category in column (8) indicates that there was a significant decline in the G inside view in the court ruling year as well, suggesting that governance practices were negatively affected by the ruling.[25] Finally, when I include the interactions between *Treat* and indicators for the years before the ruling, I find that the coefficients on these interactions are insignificant, suggesting no pre-trends in a typical difference-in-differences test (Figure IA2). By contrast, The MSCI ESG ratings do not exhibit significant changes around the ruling for treated relative to control firms (un-tabulated).

The court ruling setting also allows me to study how exogenous changes in a firm's ESG practices affect its valuation. In earlier tests, I show that both the S and G inside views are positively associated with a firm's future valuation. However, because the court ruling improved the treated firms' S inside view but degraded their G inside view, whether the firms' valuation improved after the ruling depended on whether S practices matter more for value than G practices.

Table 11 Panel B shows that after the ruling the treated firms had significant declines in valuation (Tobin's Q), despite insignificant changes in short-term profitability and sales growth, relative to the control firms. Parallel trend graphs suggest no pre-trends in these outcomes before the court ruling. These results suggest that G practices matter more for firm value than S practices, consistent with the G inside view's stronger link with firm value in the earlier tests.[26]

6. Discussion and robustness

Having established that employees provide substantial and authentic information about firms' ESG practices, I will next explore how this information correlates with existing ESG ratings and examine the implications of this relationship. Additionally, I will address the robustness of my findings, considering potential measurement and selection issues related to the inside view.

6.1. Comparing with existing ESG ratings

In this section, I discuss the correlation between the employees' ESG inside view and the existing ESG ratings by two major rating providers: MSCI (formerly KLD) and Refinitiv. Berg, Koelbel, and Rigobon

[25] Existing economic theories do suggest that improving diversity and inclusion could involve a higher organizational cost, i.e., worse governance. For example, see Lang (1986), Jackson (1992), Hambrick, Cho, and Chen (1996)).

[26] I do not control for time-varying characteristics like size or ROA. Doing so can confound the analysis since treatment may also affect those outcomes (Angrist and Pischke (2009)). Controlling for fixed characteristics like industry fixed effects and their interactions with year indicators (industry*year) do not change my results.

(2022) document that the correlations among the five widely used ESG ratings are low, averaging at 0.54. The correlations are low even though these ESG ratings take similar information sources as input (Chatterji et al. (2016), Christensen, Serafeim, and Sikochi (2021)). Thus, I expect the correlation between the inside view and the existing ESG ratings to be low too. However, since the inside view is robust to greenwashing while the existing ratings appear to rely extensively on firms' voluntary disclosure, the correlation between the inside view and the ratings may be even lower.

I find that to be the case. Table 1 Panel C shows that the rank (Spearman) correlation between the inside view and the MSCI rating is 0.00, 0.12, and 0.08 for the E, S, and G categories, respectively. The correlation is not much higher in different industries. The correlation with the ESG rating from Refinitiv is even lower.

The weak correlation between the inside view and the ESG ratings may be because employees and rating agencies care about different ESG topics. Nonetheless, this concern cannot explain my results, because I measure the inside view only on the set of ESG topics commonly considered by the major rating agencies. Moreover, when I restrict the inside view to a narrow ESG issue that both employees and rating agencies care about, namely diversity and inclusion (D&I), the inside view is still weakly correlated with a firm's ESG ratings. More D&I policies are not strongly associated with a better D&I inside view either. The Internet Appendix IA6 provides more detail.

The weak correlation could also be due to measurement noise in the inside view. I evaluate the consequences of such potential noise by testing whether my results remain similar in subsamples with likely less noise. Specifically, among firm-years with more reviews (above sample median), the rank correlation between the inside view and the MSCI rating remains low, at 0.02, 0.12, and 0.08 for the E, S, and G categories, respectively. In the subsample with a low dispersion in the inside view, i.e., when employees disagree less about their firm's ESG practices, the link between the inside view and a firm's policies and ratings remains weak. The results remain similar when I construct the inside view using only reviews with at least one ESG key word, or only reviews with a high frequency of ESG words, which are likely more informative about a firm's ESG practices. Finally, I evaluate the noise in the inside view directly by reading 500 randomly selected reviews. Among the reviews that mention ESG key words, I verify that Glassdoor's labeling of pros and cons correctly classifies positive and negative mentions of a firm's ESG practices in 92% of the cases. No systematic patterns emerge for the misclassified cases. Only one review possibly features a situation in which an employee mentions a pro-ESG practice in the cons section.

Another possibility is that the employees who write reviews on Glassdoor may not represent a firm's entire workforce well. If true, the inside view measures will be less informative about firms' ESG practices. However, I find in section 4 that the measures are highly informative. The lack of representativeness, nonetheless, could lead to a low correlation between the inside view and the existing ratings. So, I re-calculate the correlation in the subsample of firm-years with above-sample-median number of reviews relative to a firm's employee count, and find that the correlation remains under 0.15.

Overall, the inside view has a low correlation with the existing ratings, consistent with the pervasiveness of corporate greenwashing.[27]

6.2. Robustness

Beyond concerns with scope or noise of measurement, in this section, I discuss the robustness of my findings to selection concerns, other current concerns, and possible issues going forward.

6.2.1. Selection concerns

There are two groups of potential selection issues with the inside view: selection into writing a review, and selection into viewing ESG issues differently.

Regarding selection into writing a review, one common concern with online reviews is that reviews might be predominantly written by people with an extreme view, such as disgruntled employees wanting to quit their jobs. If this is true, the inside view measures could feature a lot of extremely negative values. However, Figure 1 Panel A shows that the distribution of the inside view on each ESG category is bell-shaped, featuring a low frequency of extremely negative values. The bell shape is not an artifact of my ESG word lists, as the distributions of the numerical ratings on Glassdoor are also bell-shaped (un-tabulated).

On the flip side, firms might have an incentive to boost reviews (e.g., Mayzlin, Dover, and Chevalier (2014)). Gong and Thomas (2023), in particular, infer review manipulation by the abnormal number of 5-star reviews on Glassdoor, relative to a host of firm characteristics. The presence of review manipulation may reduce the informativeness and authenticity of employees' ESG inside view. However, my baseline results show that the inside view measures are highly informative and robust to greenwashing. In addition,

[27] The correlation is even lower for firms in sin businesses (Hong and Kacperczyk (2009)) and firms with fewer analysts following, suggesting that sin businesses greenwash more and analyst monitoring can curb greenwashing.

even when excluding 5-star reviews in constructing these measures, the correlation with the baseline remains strong, exceeding 0.87 on each ESG category, and all the core results remain similar.

Another concern related to review manipulation is that employees may themselves have an incentive to greenwash their firm's image, say for better career prospects with the firm. If true, the inside view measures will not predict hard-to-manipulate ESG outcomes for a firm and will be affected by ESG cheap talk. I find the opposite in my main tests. Also, if manipulation or employee greenwashing is present at all, it should occur only with a firm's current employees, which account for 63% of my sample reviews. I find that the paper's main findings do not change when I focus on reviews only from a firm's current employees.

Regarding selection into viewing ESG issues differently, employees across different firms have differences that might induce them to write differently about ESG practices, such as differences on political leaning, job functions, skill levels, and industries in which they work. For example, employees might discuss ESG issues more in an ESG-related industry, such as oil and gas. Thus, the inside view measure could simply capture ESG-relatedness. To control for that, I have industry fixed effects and firm characteristics in all my tests. As for job title and skill level, higher-ranked and more educated employees might be more pro-ESG and write about ESG issues differently. Nonetheless, my results remain similar when I remove reviews written by high-ranked employees, as classified by their job titles using an algorithm described in the Internet Appendix IA4. Finally, as a more general way to capture individual reviewers' attitude toward ESG issues, I measure attention to ESG issues at the review level, and find that my results remain similar among the reviews featuring a high attention to ESG issues.

6.2.2. Other concerns

Another common concern with reviews data is the halo effect (Thorndike (1920)): the tendency for a reviewer's overall sentiment to affect his judgement across all rating categories. If the halo effect is prevalent among reviews, I should observe many reviews with all high or all low inside views across categories. I find no such results. Figure 1 Panel C shows that under 0.2% of reviews in my sample indicate a positive view across all three ESG categories. Under 2% of reviews indicate a positive view for two out of three ESG dimensions. The results are similar for negative views. The fraction of all-positive or all-negative reviews is also low for the numerical ratings (under 10%). Removing these reviews changes the inside view little, as the resulting measure has a correlation of 0.97 with the baseline. Lastly, only 30% of reviews have ratings that are all below 3 or all above 3, so most employees consider both the negatives and the positives in their reviews.

A concern related to the halo effect is that the inside view might merely capture how much employees like a firm. However, Section 4 shows that the inside view is significantly predictive of future ESG outcomes even after controlling for the overall rating on Glassdoor, which is a reasonable proxy for how much employees like a firm. All the predictive results remain unchanged even after controlling for all the other numerical ratings on Glassdoor, such as work-life balance rating and career prospect rating, implying that the inside view captures unique ESG information beyond the current measures on Glassdoor.

Finally, while I show that the inside view predicts future ESG-related outcomes, there may be a look-ahead bias in this finding because I use reviews in the whole sample period to construct the ESG word lists needed to measure the ESG inside view. So, in a robustness check, I use reviews only up to 2016 to construct the ESG word lists. I find that the inside view measures based on these word lists continue to significantly predict many future ESG-related outcomes, like the Best Diversity List, during the 2016-2021 period.

6.2.3. Going forward

Going forward, the informativeness and authenticity of the employees' ESG inside view may change as companies know that the inside view is being measured, a concern similar to the Lucas critique in macroeconomics (Lucas Jr (1976)). In particular, firms may try harder to manipulate employee reviews. However, the incentive to manipulate reviews has existed for many years, as review websites like Glassdoor are very popular and influential among job seekers. In addition, such an incentive was likely stronger in more recent years when Glassdoor became more popular, but I find that the inside view was informative about future outcomes in both pre- and post-2015 periods (in un-tabulated tests).

Another consideration going forward is to use larger language models (LLMs), such as BERT (Devlin et al. (2018)), to improve the measurement of the inside view beyond the *word2vec* model. Unlike BERT, the *word2vec* model cannot capture a word's multiple meanings in different contexts. However, according to Li et al. (2021), words with multiple meanings are actually quite infrequent, comprising only 12% of their full word lists. Thus, I follow their approach to retain all the words in my dictionaries.

Most importantly, the *word2vec* model is more suited to capturing employees' ESG information for three reasons. First, unlike most LLMs, the *word2vec* model does *not* require pre-training on a general corpus, allowing it to represent word meanings very specific to employee reviews by training on employee reviews only. Second, models like BERT require researchers to specify a label for the models to predict, but there is no clear existing label for ESG evaluation from the literature or rating agencies. Finally, while BERT-like models are better at performing sentiment classification, Glassdoor reviews allow me to avoid sentiment classification as employees already label review texts as pros and cons.

Finally, in the paper, I use several hard-to-manipulate ESG indicators to assess the informativeness of the inside view. This raises the question of whether we need the inside view measures beyond these existing indicators to capture a firm's authentic ESG practices. However, we still need the inside view measures because those validating indicators are very limited, covering very few firms and with little granularity. For example, whether a firm lands on the Best Diversity list is a yes-or-no indicator, and only available for up to 100 companies. In addition, these indicators are specific to some narrow ESG issues, while the inside view measure allows for broader measurement of various ESG categories.

7. Conclusion

In this paper, I analyze 10.4 million anonymous employee reviews and find that employees have useful information about firms' environmental, social, and governance (ESG) practices. Employees discuss ESG topics in 43% of reviews, thereby providing substantial information about firms' ESG practices. The employees' inside view predicts various hard-to-manipulate indicators of a firm's future ESG-related outcomes, beyond the existing ESG ratings, on all the ESG dimensions, with the most impressive power on the G dimension. Furthermore, the inside view shows robustness to ESG cheap talk, as low-cost changes in a firm's ESG policies do not affect the inside view, while more expensive changes do.

This paper has important implications for both industry practices and academic research. For industry practices, investors and rating agencies should not take firms' voluntary disclosure at face value in assessing their ESG practices. In addition, ESG rating agencies could consider incorporating employee reviews into their rating methodology more broadly. For future research, researchers can examine the reasons for and implications of the gap between external ESG ratings and the inside view. Moreover, since employee reviews cover both public and private firms, future research can study whether public ownership affects ESG practices. Finally, my approach of measuring ESG practices could be generalized to measuring traditionally hard-to-measure issues, such as discrimination and fraud.

References

Aggarwal, Reena, Isil Erel, René Stulz, and Rohan Williamson, 2009, Differences in Governance Practices Between U.S. and Foreign Firms: Measurement, Causes, and Consequences, *Review of Financial Studies* 22, 3131–3169.

Angrist, Joshua D., and Jörn-Steffen Pischke, 2009, *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton university press).

Baier, Philipp, Marc Berninger, and Florian Kiesel, 2020, Environmental, Social and Governance Reporting in Annual Reports: A Textual Analysis, *Financial Markets, Institutions & Instruments* 29, 93–118.

Baker, Andrew C., David F. Larcker, and Charles C.Y. Wang, 2022, How Much Should We Trust Staggered Difference-in-Differences Estimates?, *Journal of Financial Economics* 144, 370–395.

Baker, Andrew, David F. Larcker, Charles McClure, Durgesh Saraph, and Edward M. Watts, 2023, Diversity Washing, *Chicago Booth Research Paper*.

Bebchuk, Lucian A., Kobi Kastiel, and Roberto Tallarita, 2023, Stakeholder Capitalism in the Time of COVID, *Forthcoming, Yale Journal on Regulation* 40.

Bebchuk, Lucian A., and Roberto Tallarita, 2020, The Illusory Promise of Stakeholder Governance, *Cornell L. Rev.* 106, 91.

Bebchuk, Lucian A., and Roberto Tallarita, 2022, Will Corporations Deliver Value to All Stakeholders?, *Forthcoming, Vanderbilt Law Review* 75.

Bebchuk, Lucian, Alma Cohen, and Allen Ferrell, 2009, What Matters in Corporate Governance?, *The Review of financial studies* 22, 783–827.

Berg, Florian, Kornelia Fabisik, and Zacharias Sautner, 2021, Rewriting History II: The (Un)predictable Past of ESG Ratings, *Working Paper*.

Berg, Florian, Julian F. Koelbel, and Roberto Rigobon, 2022, Aggregate Confusion: The Divergence of ESG Ratings, *Review of Finance* 26, 1315–1344.

Berg, Florian, Julian F Kölbel, Anna Pavlova, and Roberto Rigobon, 2023, ESG Confusion and Stock Returns: Tackling the Problem of Noise, *National Bureau of Economic Research*.

Bertomeu, J, E Cheynel, E Floyd, and W Pan, 2021, Using Machine Learning to Detect Misstatements, *Review of Accounting Studies*.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, 2004, How Much Should We Trust Differences-in-Differences Estimates?, *The Quarterly Journal of Economics* 119, 249–275.

Bessec, Marie, and Julien Fouquau, 2021, Green Sentiment in Financial Markets: A Global Warning, *Working Paper*.

Bloom, Nicholas, Tarek Alexander Hassan, Aakash Kalyani, Josh Lerner, and Ahmed Tahoun, 2021, The Diffusion of Disruptive Technologies, National Bureau of Economic Research.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bonelli, Maxime, Marie Brière, and François Derrien, 2022, Do Employees Care about ESG? Evidence from Employee Share Plans, *Working Paper*.

Campbell, Dennis, and Ruidi Shang, 2021, Tone at the Bottom: Measuring Corporate Misconduct Risk from the Text of Employee Reviews, *Management Science: Forthcoming*.

Chatterji, Aaron K., Rodolphe Durand, David I. Levine, and Samuel Touboul, 2016, Do Ratings of Firms Converge? Implications for Managers, Investors and Strategy Researchers, *Strategic Management Journal* 37, 1597–1614.

Chava, Sudheer, Wendi Du, and Baridhi Malakar, 2021, Do Managers Walk the Talk on Environmental and Social Issues?, *Available at SSRN 3900814*.

Cho, Young Jun, Jungbae Kim, Holly Yang, and Mengjie Yang, 2024, Corporate Disclosures for Green Supply Chains: Evidence from Scope 3 Emissions Disclosure, .

Christensen, Dane M., George Serafeim, and Anywhere Sikochi, 2021, Why is Corporate Virtue in the Eye of The Beholder? The Case of ESG Ratings, *The Accounting Review* 97, 147–175.

Colonnelli, Emanuele, Timothy McQuade, Gabriel Ramos, Thomas Rauter, and Olivia Xiong, 2023, Polarizing Corporations: Does Talent Flow to" Good" Firms?, National Bureau of Economic Research.

Cong, Lin William, Tengyuan Liang, and Xiao Zhang, 2019, Textual Factors: A Scalable, Interpretable, and Data-driven Approach to Analyzing Unstructured Information, *Working Paper*.

Cornaggia, Jess, and Kimberly Cornaggia, 2023, ESG Ratings Management, *Available at SSRN 4520688*.

Dechezleprêtre, Antoine, Adrien Fabre, Tobias Kruse, Bluebery Planterose, Ana Sanchez Chico, and Stefanie Stantcheva, 2022, Fighting Climate Change: International Attitudes Toward Climate Policies, National Bureau of Economic Research.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, 2018, BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding, *arXiv preprint arXiv:1810.04805*.

Douglas, Elyse, Tracy Van Holt, and Tensie Whelan, 2017, Responsible Investing: Guide to ESG Data Providers and Relevant Trends, *Journal of Environmental Investing* 8, 91–114.

Dube, Svenja, and Chenqi Zhu, 2021, The Disciplinary Effect of Social Media: Evidence from Firms' Responses to Glassdoor Reviews, *Journal of Accounting Research* 59, 1783–1825.

Duchin, Ran, Janet Gao, and Qiping Xu, 2022, Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution, *Available at SSRN*.

Dyck, Alexander, Karl V. Lins, Lukas Roth, and Hannes F. Wagner, 2019, Do Institutional Investors Drive Corporate Social Responsibility? International Evidence, *Journal of Financial Economics* 131, 693–714.

Edmans, Alex, 2009, Blockholder Trading, Market Efficiency, and Managerial Myopia, *The Journal of Finance* 64, 2481–2513.

Edmans, Alex, 2011, Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices, *Journal of Financial Economics* 101, 621–640.

Edmans, Alex, 2012, The Link Between Job Satisfaction and Firm Value, with Implications for Corporate Social Responsibility, *Academy of Management Perspectives* 26, 1–19.

Edmans, Alex, 2023, The End of ESG, *Financial Management* 52, 3–17.

Gao, Lei, Jie Jack He, and Juan Julie Wu, 2021, Standing Out from the Crowd Via CSR Engagement: Evidence from Non-Fundamental-Driven Price Pressure, *Journal of Financial and Quantitative Analysis*, 1–50.

Gibson Brandon, Rajna, Simon Glossner, Philipp Krueger, Pedro Matos, and Tom Steffen, 2022, Do Responsible Investors Invest Responsibly?, *Review of Finance* 26, 1389–1432.

Giglio, Stefano, Theresa Kuchler, Johannes Stroebel, and Xuran Zeng, 2023, Biodiversity Risk, National Bureau of Economic Research.

Gillan, Stuart L., Andrew Koch, and Laura T. Starks, 2021, Firms and Social Responsibility: A Review of ESG and CSR Research in Corporate Finance, *Journal of Corporate Finance* 66, 101889.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate Governance and Equity Prices, *The Quarterly Journal of Economics* 118, 107–156.

Gong, Ping, and Jacob K. Thomas, 2023, Thumb on the Scale: Do Employers Manage Glassdoor Reviews?, *Available at SSRN 4460625*.

Goodman-Bacon, Andrew, 2021, Difference-in-Differences with Variation in Treatment Timing, *Journal of Econometrics* 225, 254–277.

Green, T. Clifton, Ruoyan Huang, Quan Wen, and Dexin Zhou, 2019, Crowdsourced Employer Reviews and Stock Returns, *Journal of Financial Economics* 134, 236–251.

Grewal, Jody, and George Serafeim, 2020, Research on Corporate Sustainability: Review and Directions for Future Research, *Foundations and Trends® in Accounting* 14, 73–127.

Gu, Lifeng, and Dirk Hackbarth, 2021, Inflexibility and Leverage, *Working Paper*.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2015, The Value of Corporate Culture, *Journal of Financial Economics* 117, 60–76.

Guo, Feng, Chenxi Lin, Adi Masli, and Michael S. Wilkins, 2021, Auditor Responses to Shareholder Activism, *Contemporary Accounting Research* 38, 63–95.

Hacamo, Isaac, 2022, Prejudice in the Workplace and Firm Revenue, *SSRN Electronic Journal*.

Hambrick, Donald C., Theresa Seung Cho, and Ming-Jer Chen, 1996, The Influence of Top Management Team Heterogeneity on Firms' Competitive Moves, *Administrative science quarterly*, 659–684.

Hanley, Kathleen Weiss, and Gerard Hoberg, 2019, Dynamic Interpretation of Emerging Risks in the Financial Sector, *The Review of Financial Studies*.

Hassan, Tarek A, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, 2019, Firm-Level Political Risk: Measurement and Effects*, *The Quarterly Journal of Economics* 134, 2135–2202.

Heath, Davidson, Daniele Macciocchi, Roni Michaely, and Matthew C. Ringgenberg, 2023, Does Socially Responsible Investing Change Firm Behavior?, *Review of Finance*.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy* 124, 1423–1465.

Hoepner, Andreas G. F., Ioannis Oikonomou, Zacharias Sautner, Laura T. Starks, and Xiaoyan Zhou, 2020, ESG Shareholder Engagement and Downside Risk, *SSRN Electronic Journal*.

Hong, Harrison, and Marcin Kacperczyk, 2009, The Price of Sin: The Effects of Social Norms on Markets, *Journal of Financial Economics* 93, 15–36.

Hvidberg, Kristoffer B., Claus T. Kreiner, and Stefanie Stantcheva, 2023, Social Positions and Fairness Views on Inequality, *Review of Economic Studies* 90, 3083–3118.

Jackson, Susan E., 1992, Consequences of Group Composition for the Interpersonal Dynamics of Strategic Issue Processing, *Advances in Strategic Management* 8, 345–382.

Jensen, C, and H Meckling, 1976, Theory of The Firm: Managerial Behavior, Agency Costs And Ownership Structure, *Journal of Financial Economics*, 56.

Ji, Yuan, Oded Rozenbaum, and Kyle Welch, 2017, Corporate Culture and Financial Reporting Risk: Looking Through the Glassdoor, *Available at SSRN 2945745*.

Kamiya, Shinichi, Jun-Koo Kang, Jungmin Kim, Andreas Milidonis, and René M. Stulz, 2021, Risk Management, Firm Reputation, and the Impact of Successful Cyberattacks on Target Firms, *Journal of Financial Economics* 139, 719–749.

Klein, April, and Emanuel Zur, 2009, Entrepreneurial Shareholder Activism: Hedge Funds and Other Private Investors, *The Journal of Finance* 64, 187–229.

Koren, Miklós, and Rita Peto, 2020, Business Disruptions from Social Distancing, *Plos one* 15.

Krueger, Philipp, Daniel Metzger, and Jiaxin Wu, 2023, The Sustainability Wage Gap, *Swedish House of Finance Research Paper*, 21–17.

Lang, Kevin, 1986, A Language Theory of Discrimination, *The Quarterly Journal of Economics* 101, 363–382.

Lee, Yoojin, Shaphan Ng, Terry Shevlin, and Aruhn Venkat, 2021, The Effects of Tax Avoidance News on Employee Perceptions of Managers and Firms: Evidence from Glassdoor.com Ratings, *The Accounting Review* 96, 343–372.

Li, Jun, and Di (Andrew) Wu, 2020, Do Corporate Social Responsibility Engagements Lead to Real Environmental, Social, and Governance Impact?, *Management Science* 66, 2564–2588.

Li, Kai, Feng Mai, Rui Shen, and Xinyan Yan, 2021, Measuring Corporate Culture Using Machine Learning, *The Review of Financial Studies* 34, 3265–3315.

Loughran, Tim, and Bill McDonald, 2016, Textual Analysis in Accounting and Finance: A Survey, *Journal of Accounting Research* 54, 1187–1230.

Lucas Jr, Robert E., 1976, Econometric Policy Evaluation: A Critique, *Carnegie-Rochester conference series on public policy* (North-Holland).

Marinescu, Ioana, Andrew Chamberlain, Morgan Smart, and Nadav Klein, 2021, Incentives Can Reduce Bias in Online Employer Reviews., *Journal of Experimental Psychology: Applied* 27, 393.

Matos, Pedro, 2020, ESG and Responsible Institutional Investing Around the World: A Critical Review, *CFA Institute Research Foundation*.

Mayzlin, Dina, Yaniv Dover, and Judith Chevalier, 2014, Promotional Reviews: An Empirical Investigation of Online Review Manipulation, *American Economic Review* 104, 2421–2455.

Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean, 2013, Distributed Representations of Words and Phrases and Their Compositionality, *Advances in Neural Information Processing Systems*.

Moffitt, Jacquelyn Sue, Jeanne-Claire Alyse Patin, and Luke Watson, 2023, Corporate Environmental, Social, and Governance (ESG) Performance and the Internal Control Environment, *Accounting Horizons*, 1–22.

Raghunandan, Aneesh, and Shiva Rajgopal, 2021, Do Socially Responsible Firms Walk the Talk?, *SSRN Electronic Journal*, 45.

Riley, John G., 1979, Informational Equilibrium, *Econometrica* 47, 331–359.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang, 2023, Firm-Level Climate Change Exposure, *The Journal of Finance* 78, 1449–1498.

Sheng, Jinfei, 2022, Asset Pricing in the Information Age: Employee Expectations and Stock Returns, *Available at SSRN 3321275*.

Spence, Michael, 1973, Job Market Signaling, *The Quarterly Journal of Economics* 87, 355–374.

Tang, Dragon Yongjun, Jiali Yan, and Chelsea Yaqiong Yao, 2022, The Determinants of ESG Ratings: Rater Ownership Matters, *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI-ESSEC*.

Thorndike, Edward L., 1920, A Constant Error in Psychological Ratings, *Journal of Applied Psychology* 4, 25–29.

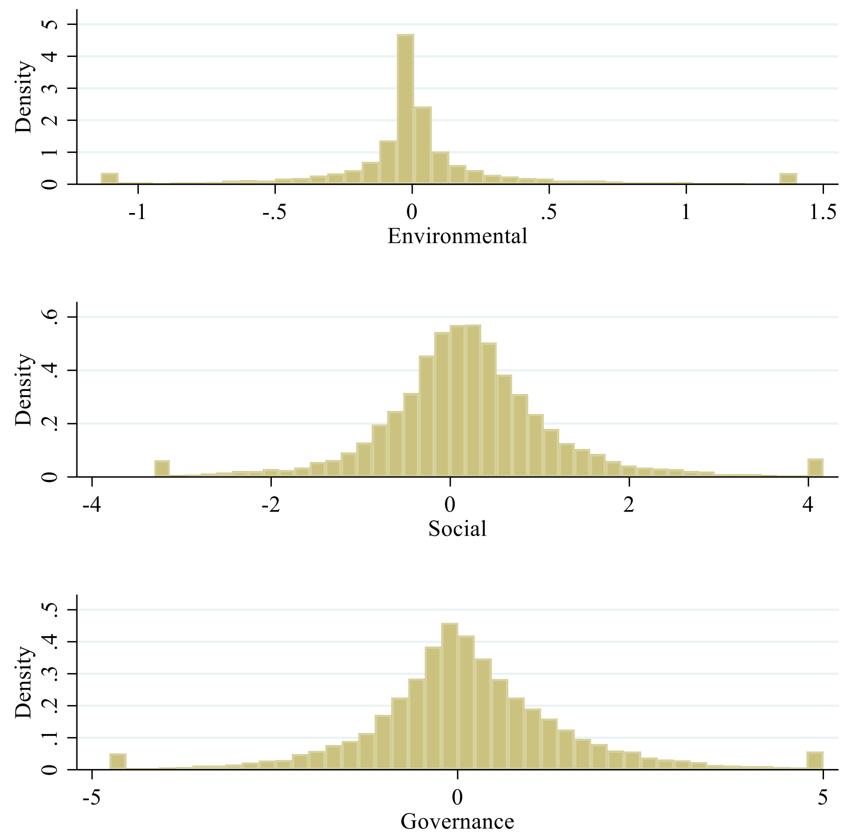
Welch, Kyle, and Aaron Yoon, 2020, Do High Ability Managers Choose ESG Projects that Create Shareholder Value? Evidence from Employee Opinions, *SSRN Journal*.

Wong, Christina, Aiste Brackley, and Erika Petoy, 2019, Rate the Raters 2019, *Sustainability.com*.

Figure 1: Distribution of ESG inside views

In this figure, Panel A plots the histogram for the inside view on each ESG category at the firm-year level. In constructing these histograms, I exclude firm-years with no mentioning of ESG topics in their reviews. The inside view measure at the firm-year level is the average inside view measure across reviews in that firm-year. The inside view measure at the review level is the percentage of E, S, or G words in the review's pros relative to cons sections. Panel B shows the percentages of reviews in my sample that have all positive or all negative views or ratings across categories.

Panel A: Distribution of ESG inside views



Panel B: The percentage of all positive or all negative reviews

	N	Percentage
Mentioning at least one ESG word	2,444,040	42.74
All positive on E, S, and G	2,444,040	0.03
All negative on E, S, and G	2,444,040	0.10
Positive 2 out of 3 E-S-G	2,444,040	1.91
Negative 2 out of 3 E-S-G	2,444,040	2.92
All numerical ratings are 5	2,444,040	9.05
All numerical ratings are 1	2,444,040	2.60
All ratings above 3	2,444,040	24.99
All ratings below 3	2,444,040	6.18

Table 1: Summary statistics

This table presents summary statistics for the main variables in the paper. Panel A presents summary statistics at the firm-year level, for my sample of publicly listed firms. Panel B presents summary statistics at the review level, also on the sample of public firms. Panel C repeats Panel B, but on the full sample of over 10 million reviews, so it includes reviews for both public and private companies. Panel D presents the rank (Spearman) correlation between the inside view and the ESG rating from either MSCI or Refinitiv at the firm-year level for each of the ESG categories and the combined (equally weighted) ESG score across the ESG categories. The correlations are performed on the sample of public firms only, because the MSCI ratings and the Refinitiv ESG ratings cover only public firms. Panel D also lists the correlations in different industries under the Fama-French five industry classification. See the Internet Appendix for variable description.

Panel A: Summary statistics at the firm-year level

	N	Mean	Std. Dev.	p10	Median	p90
No. of reviews	22186	108.46	360.30	3	28	206
Inside view E	22186	.01	0.27	-.11	0	.12
Inside view S	22186	.19	1.03	-.82	.09	1.28
Inside view G	22186	.12	1.43	-1.36	0	1.75
MSCI rating of E	12225	.21	0.48	0	0	1
MSCI rating of S	12224	.12	0.73	-1	0	1
MSCI rating of G	12005	-.1	0.52	-1	0	0
Scope 3 emission disclosure	25998	.11	0.32	0	0	1
Log(total emissions)	5299	12.95	2.42	10.09	12.79	16.28
Fortune Best Companies indicator	25998	.02	0.13	0	0	0
Best Diversity indicator	9285	.02	0.13	0	0	0
Number of IC weaknesses	20462	.16	1.21	0	0	0
Misstatement risk	16229	.05	0.06	.01	.03	.08
Shareholder activism filings	20507	.1	0.44	0	0	0
Tobin's Q	17976	2.09	1.53	.99	1.56	3.83
Downside volatility	19170	.02	0.01	.01	.02	.03
Tail risk	19177	.08	0.05	.03	.06	.13
Yearly buy-and-hold return	19177	.05	0.46	-.45	.1	.5
Institutional ownership	18125	.73	0.25	.36	.81	.98
Entrenchment index	14165	3.26	0.86	2	3	4
Leverage	20020	.29	0.26	0	.24	.69
Tobin's Q	17976	2.09	1.53	.99	1.56	3.83
Sales growth	19375	.06	0.19	-.12	.05	.27
Cash/assets	20085	.16	0.17	.01	.1	.42
Glassdoor overall rating	22186	3.23	0.64	2.46	3.24	4
BRT	25998	.08	0.27	0	0	0
UNGC	25998	.04	0.20	0	0	0

Panel B: Summary statistics at the review level - public firms sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Review contains ESG word	2444040	0.43	0.49	0.00	1.00
Review contains E word	2444040	0.02	0.13	0.00	1.00
Review contains S word	2444040	0.24	0.42	0.00	1.00
Review contains G word	2444040	0.28	0.45	0.00	1.00
Word count - Pros	2444040	17.20	22.57	0.00	2311.00
Word count - Cons	2444040	27.57	49.57	1.00	4917.00
Word count - Total	2444040	44.77	61.41	2.00	5030.00
Inside view E	2444038	-0.00	1.04	-80.00	60.00
Inside view S	2444038	0.28	4.24	-100.00	100.00
Inside view G	2444038	0.33	5.28	-100.00	100.00
Employee high-ranked	2444040	0.17	0.38	0.00	1.00
Overall rating not extreme	2444040	0.67	0.47	0.00	1.00

Panel C: Summary statistics at the review level – all 10.4 million reviews

Variable	Obs	Mean	Std. Dev.	Min	Max
Review contains ESG word	10425402	0.44	0.50	0.00	1.00
Review contains E word	10425402	0.02	0.14	0.00	1.00
Review contains S word	10425402	0.25	0.43	0.00	1.00
Review contains G word	10425402	0.29	0.46	0.00	1.00
Word count - Pros	10425401	20.14	29.64	0.00	3342.00
Word count - Cons	10425401	28.95	53.73	0.00	6545.00
Word count - Total	10425401	49.09	68.16	2.00	6558.00
Inside view E	10425390	0.01	1.09	-100.00	100.00
Inside view S	10425390	0.24	4.08	-100.00	100.00
Inside view G	10425390	0.21	5.10	-100.00	100.00
Employee high-ranked	10425401	0.17	0.37	0.00	1.00
Overall rating not extreme	10425402	0.59	0.49	0.00	1.00

Panel D: Correlation between the inside view and major ESG ratings

Correlation with the MSCI ESG rating

	Full sample	Consumer	Manufacturing	High tech	Healthcare	Others
ESG	0.13***	0.12***	0.05**	0.18***	0.10***	0.16***
E	0.00	-0.02	-0.02	0.07***	-0.01	-0.02
S	0.12***	0.12***	0.06***	0.14***	0.14***	0.12***
G	0.08***	0.07***	0.02	0.12***	0.05	0.10***

Correlation with the Refinitiv ESG rating

	Full sample	Consumer	Manufacturing	High tech	Healthcare	Others
ESG	0.07***	0.10***	0.08***	0.04**	0.02	0.13***
E	0.00	-0.04*	0.01	0.05**	-0.06	-0.01
S	0.11***	0.11***	0.10***	0.08***	0.12***	0.13***
G	0.01	0.03	0.00	0.03	0.01	0.03*

*** p<.01, ** p<.05, * p<.1*

Table 2: ESG word lists

Panel A presents the seed word lists on ESG topics. I obtain these lists by selecting the most frequently used words and phrases across ESG rating methodologies and select academic papers, as detailed in Section 3.2. Panel B presents the 50 words and phrases with the highest cosine similarity with the average vector representing each ESG category's seed word list. The full ESG dictionaries are available on the author's webite.

Panel A: Seed word lists

Environmental	Social	Governance
environmental, emission, energy, water, carbon, biodiversity, pollution, green, packaging, renewable, recycle, footprint, disposal, greenhouse, raw material, renewable energy, carbon footprint, oil spill, global footprint, global warming, environmental protection, environmental sustainability, noise pollution, fossil fuel, electric vehicle, solar energy, solar panel, plastic bag, air pollution, wind turbine, nuclear power, natural gas	human, employee, health, safety, labor, community, labour, social, relation, philanthropy, workforce, citizenship, occupational, human capital, corporate citizenship, occupational health, community involvement, race ethnicity, discrimination harassment, medicaid medicare, collective bargaining, human resource, age discrimination, gender racial, racial ethnic, unfair dismissal, human trafficking, threat violence, charitable donation, charitable giving	board, governance, shareholder, ethic, practice, corruption, instability, bribery, committee, executive, transparency, ownership, audit, level, diversity, business, code conduct, board director, insider trading, daytoday operation, tax evasion, money laundering, policy procedure, regulatory scrutiny, track record, unethical behavior, law violation, nepotism cronyism

Panel B: Top 50 words added

Environmental	Social	Governance
co2, biofuel, hydrocarbon, irrigation, fertilizer, ethanol, agricultural, pollutant, recycling, purification, geothermal, ammonia, herbicide, fracke, ecological, thermal, forestry, electricity, dioxide, pesticide, hydroelectric, petrochemical, landfill, mining, consumption, compost, agriculture, compressor, lubricant, chemical, nuclear, biodegradable, gas turbine, polymer, lng, wastewater, aluminium, recyclable, contamination, industrial, electric utility, filtration, biomass, synthetic, vegetation, ewaste, reservoir, coolant, groundwater, stormwater	advocacy, sustainability, social justice, diversity inclusion, environmental protection, stewardship, equality, inclusion diversity, environmental sustainability, inclusion, eeo, humanitarian, awareness, diversity equality, justice, society, representation, gender equality, refugee, antidiscrimination, outreach, cultural competency, reproductive health, indigenous, antiracism, community outreach, glbt, environmental stewardship, mental health, racial justice, racial equity, nondiscrimination, systemic racism, domestic violence, prevention, racial gender, safeguard, hivaid, consciousness, constitutional, hiv, participant, latino, lgbtq, antibullye, cultural diversity, volunteerism, hse, dei, anticorruption	leadership, compliance, malfeasance, institutional, doj, organization, legal compliance, regulator, unethical practice, stakeholder, cronyism, integrity, embezzlement, regulatory compliance, impropriety, noncompliance, accountability, csuite, conflict interest, organizational, regulatory, strategic, fraudulent activity, partnership, due diligence, cfpb, risk aversion, operational, decisionmake, council, systemic, strategic planning, misuse fund, misconduct, irresponsibility, cronyism nepotism, political correctness, indict, discriminatory practice, ethical, opacity, mismanagement, bod, antitrust, decision making, watchdog, entity, governmental, ftc, misappropriation

Table 3: Top and bottom firms by the inside view

In this table, Panel A shows the top 5 firms and bottom 5 firms based on their average inside view of E, S, or G practices between 2014 and 2018. Before ranking the firms, I restrict the sample to the largest 500 firms by the average total assets between 2014 and 2018. Panel B shows excerpts from two actual reviews of the top and bottom firms in each category. These excerpts are from the pros (for the top firms) and the cons (for the bottom firms) of the reviews.

Panel A: Top and bottom firms

Ranked by employees' inside view of ESG practices		
Environmental	**Social**	**Governance**
Top 5		
Sunedison	Umpqua Bank	Linkedin
American Water	Old National Bancorp	Salesforce
Nextera Energy, Inc.	Gap Inc.	Yum!
Portland General Electric	Investors Bank	Microchip Technology
Albemarle	CNO Financial Group	Ceridian
Bottom 5		
ConocoPhillips	Opus Bank	FirstEnergy
Alpha Natural Resources	Intercontinental Exchange	Laureate Education
Freeport-Mcmoran	Tenneco	FirstMerit
Altria	Precision Castparts	Capital Bank
Pioneer Natural Resources	Pepco Holdings	Sterling Bancorp

Panel B: Select reviews from the top and bottom firms.

Company	Employee title	Year	Glassdoor overall rating	Select text
Top E - Sunedison	Business Development	2015	5.0	The company has excellent potential to capture market share in a rapidly growing sector (**renewable energy**). With the recent acquisition of First Wind the company is now expanding beyond **solar into wind energy**. Combined with our work on **energy storage technology** ...
	Project Engineer	2014	1.0	**It's solar**. Great way to help **the world's energy shortage** and **go green**. Some very excellent and helpful employees…
Bottom E - Pioneer Natural Resources	Anonymous Employee	2016	4.0	They need to do more core analysis and research for better **reservoir characterization.**
	Operations Technician	2015	4.0	**Poor management in Field Operations**. Going through a change in focus currently by shifting focus to **horizontal drilling**…
Top S - Umpqua Bank	Universal Associate	2015	4.0	Listens to **employees**, **community involvement**, rewards for performance.
	Accountant III	2017	5.0	**Paid 40 Hours** Annually to **Volunteer in the Community**. Treats you like a professional not Micro-managing.
Bottom S - Pepco Holdings	Anonymous Employee	2015	4.0	Work ethics and bad management . **No gender equality**.
	Tax Accountant	2016	5.0	Management doesn't listen to lower-level employees, **too many hours** are required to be worked, **bad work life balance**
Top G - Linkedin	Sales	2014	4.0	... Jeff Weiner is an inspiration, and the other execs are all driving towards a **shared vision**. The **culture and values** of the company are held in high esteem and they're **felt throughout** the organizations…
	Anonymous Employee	2017	5.0	**Company values and adherence** to them (be open, honest & constructive). **Transparency** is not just a word; it's shown in actions by the executive team. The **outstanding leadership** team and commitment to **developing leaders** within the company…
Bottom G - Sterling Bancorp	Client Service Associate	2018	2.0	Too much **pressure for sales**; Don’t care about employees; Horrendous **leadership**
	Client Service	2016	1.0	Very **disorganized**. Your **work ethic** will not go a long way

Table 4: Predicting future environmental performance indicators.

This table shows the regressions at the firm-year level of environmental (E) performance indicators in year t+1, t+2, or t+3 on the E inside view and the MSCI E rating at year t. The dependent variable is an indicator whether a firm discloses its Scope 3 CO_2 equivalent emissions in a year in Panel A, and the logarithm of total emissions for Panel B. Total emissions is the sum of all Scopes of emissions a firm discloses in a year. The models underlying all regressions are either OLS for continuous dependent variables, or Logit for indicator dependent variables. All regressions include as controls: Fama-French 48 industry fixed effects, year fixed effects, size, and operating performance (ROA), following Li et al. (2021), all measured at year t. All variables except for indicator variables are standardized to have a zero mean and a unit standard deviation. Standard errors (in parentheses) are clustered by firms.

Panel A: Predicting whether a firm discloses Scope 3 emissions.

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view E	.07**	.08**	.09***	.05	.07**	.08**	.06*	.06*	.06**
	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
MSCI E		.6***	.59***		.54***	.53***		.49***	.47***
		(.05)	(.05)		(.05)	(.05)		(.05)	(.05)
Overall rating			.27***			.28***			.25***
			(.06)			(.06)			(.06)
Observations	15653	10789	10789	14235	10788	10788	12798	9632	9632
Pseudo R^2	.34	.37	.38	.33	.36	.36	.33	.35	.35
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel B: Predicting Log(total emissions).

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view E	-.01**	-.02***	-.02***	-.01**	-.02**	-.02**	-.01*	-.02**	-.02**
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
MSCI E		-.02	-.02		-.01	-.01		-.01	-.01
		(.01)	(.01)		(.01)	(.01)		(.01)	(.01)
Overall rating			-.04**			-.04*			-.03*
			(.02)			(.02)			(.02)
Observations	4685	3511	3511	4363	3837	3837	4007	3475	3475
R-squared	.77	.78	.78	.76	.77	.77	.76	.76	.76
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 5: Predicting future social performance indicators.

This table shows the regressions at the firm-year level of social (S) performance indicators in year t+1, t+2, or t+3 on the inside view on S practices and the MSCI S rating at year t. The dependent variable is an indicator whether a firm is in the Fortune's Best 100 Companies to Work For in a year for Panel A, and an indicator whether a firm is in the Best Companies for Diversity list in a year for Panel B. All regressions are estimated with Logit. All regressions include as controls: Fama-French 48 industry fixed effects, year fixed effects, size, and operating performance (ROA), following Li et al. (2021), all measured at year t. All variables except for indicator variables are standardized to have a zero mean and a unit standard deviation. Standard errors (in parentheses) are clustered by firms.

Panel A: Predicting whether firm lands in Fortune Best 100 Companies list.

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view S	0.55***	0.53***	0.34***	0.51***	0.50***	0.30***	0.45***	0.42***	0.25***
	(0.07)	(0.09)	(0.09)	(0.07)	(0.08)	(0.09)	(0.07)	(0.09)	(0.09)
MSCI S		1.20***	1.30***		1.10***	1.21***		1.03***	1.09***
		(0.13)	(0.14)		(0.13)	(0.14)		(0.15)	(0.17)
Overall rating			1.45***			1.51***			1.36***
			(0.14)			(0.14)			(0.13)
Observations	12033	8101	8101	10812	7983	7983	9489	6940	6940
Pseudo R^2	0.16	0.23	0.32	0.16	0.20	0.31	0.15	0.19	0.28
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel B: Predicting whether firm lands in Best Companies for Diversity list.

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view S	0.91***	0.93***	0.67***	0.87***	0.82***	0.54***	0.66***	0.69***	0.47***
	(0.14)	(0.16)	(0.17)	(0.13)	(0.15)	(0.14)	(0.12)	(0.14)	(0.14)
MSCI S		0.27	0.31		0.30	0.33		0.31	0.28
		(0.18)	(0.20)		(0.19)	(0.21)		(0.21)	(0.22)
Overall rating			1.48***			1.50***			1.09***
			(0.23)			(0.24)			(0.19)
Observations	4843	3523	3523	4820	3418	3418	4722	3209	3209
Pseudo R^2	0.19	0.20	0.27	0.19	0.19	0.26	0.17	0.17	0.22
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 6: Predicting future governance quality indicators.

This table shows the regressions at the firm-year level of governance performance indicators in year t+1, t+2, or t+3 on the inside view of governance practices and the MSCI governance rating at year t. The dependent variable is the number of internal control weaknesses in Panel A, the probability of a firm having a misstatement (misstatement risk, Bertomeu et al. (2021)) in Panel B, and the number of shareholder activism filings in Panel C. All regressions are Logit for indicator dependent variables, Poisson for count dependent variables, and OLS otherwise. All regressions include as controls: Fama-French 48 industry fixed effects, year fixed effects, size, and operating performance (ROA), following Li et al. (2021), all measured at year t. Detailed variable descriptions are in Appendix B. All variables except for indicator variables and count variables are standardized to have a zero mean and a unit standard deviation. Standard errors (in parentheses) are clustered by firms.

Panel A: Predicting Number of Internal Control Weaknesses.

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view G	-.39***	-.27***	-.24***	-.26***	-.21***	-0.15*	-.25***	-.23***	-0.20**
	(0.06)	(0.08)	(0.08)	(0.06)	(0.07)	(0.08)	(0.06)	(0.08)	(0.08)
MSCI G		0.00	0.01		0.14*	0.15**		0.01	0.01
		(0.11)	(0.11)		(0.08)	(0.08)		(0.10)	(0.10)
Overall rating			-0.12			-0.20**			-0.12
			(0.08)			(0.09)			(0.09)
Observations	15411	10453	10453	13689	10306	10306	12013	8815	8815
Pseudo R^2	0.11	0.12	0.12	0.11	0.11	0.12	0.10	0.11	0.11
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel B: Predicting Misstatement Risk.

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view G	-.04***	-.03***	-0.01	-.05***	-.04***	-.03***	-.04***	-.04***	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MSCI G		-0.01	-0.01		0.01	0.01		0.01	0.01
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
Overall rating			-.06***			-0.02*			-0.03**
			(0.01)			(0.01)			(0.02)
Observations	13203	10392	10392	11891	9232	9232	10341	7983	7983
R-squared	0.09	0.08	0.09	0.08	0.07	0.08	0.08	0.07	0.07
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel C: Predicting Number of Shareholder Activism Filings.

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view G	-.14***	-0.05	-0.01	-.11***	-0.07	-0.01	-.18***	-.13***	-0.10**
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)
MSCI G		0.08	0.08		-0.03	-0.02		-0.04	-0.03
		(0.06)	(0.06)		(0.07)	(0.07)		(0.07)	(0.07)
Overall rating			-0.13**			-.19***			-0.09*
			(0.05)			(0.06)			(0.05)
Observations	15643	10406	10406	13984	10244	10244	12295	9155	9155
Pseudo R^2	0.08	0.06	0.06	0.08	0.07	0.07	0.08	0.08	0.08
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 7: Predicting future financial performance indicators.

This table shows the regressions at the firm-year level of financial performance indicators in year t+1, t+2, or t+3 on the inside view of governance practices and the MSCI governance rating at year t. The dependent variable is Tobin's Q (a valuation ratio) in Panel A, downside risk (the average absolute value of the lowest 5 percent of daily returns in a year) in Panel B, and stock return (buy and hold return in a calendar year) in Panel C. All regressions are estimated by OLS. All regressions include as controls: Fama-French 48 industry fixed effects, year fixed effects, size, and operating performance (ROA), following Li et al. (2021), all measured at year t. Detailed variable descriptions are in Appendix B. All variables except for indicator variables and count variables are standardized to have a zero mean and a unit standard deviation. Standard errors (in parentheses) are clustered by firms.

Panel A: Predicting Tobin's Q (valuation)

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view E	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inside view S	0.03***	0.03***	0.00	0.03***	0.02**	-0.01	0.03***	0.02**	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inside view G	0.14***	0.11***	0.06***	0.12***	0.10***	0.06***	0.11***	0.10***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MSCI E		0.05***	0.04***		0.05***	0.05***		0.05***	0.04***
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
MSCI S		0.06***	0.05***		0.06***	0.05***		0.07***	0.06***
		(0.01)	(0.01)		(0.01)	(0.01)		(0.02)	(0.02)
MSCI G		-0.02**	-0.02**		-.03***	-.03***		-0.01	-0.01
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
Overall rating			0.16***			0.16***			0.14***
			(0.02)			(0.02)			(0.02)
Observations	14626	10059	10059	13045	9909	9909	11434	8728	8728
R-squared	0.23	0.28	0.30	0.22	0.26	0.28	0.21	0.25	0.27
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel B: Predicting Downside Risk

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view E	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inside view S	-0.00	0.00	0.00	0.01	0.01	0.01*	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inside view G	-.04***	-0.01**	-0.01	-.03***	-.02***	-0.02**	-.03***	-.03***	-.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MSCI E		-0.01	-0.01		-0.01	-0.01		-0.01	-0.01
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
MSCI S		-0.01	-0.01		-0.02*	-0.02*		-0.02**	-0.02**
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
MSCI G		-0.02**	-0.02**		-0.01	-0.01		-0.01	-0.01
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
Overall rating			-0.01			-0.02*			-0.02**
			(0.01)			(0.01)			(0.01)
Observations	15414	10623	10623	13776	10497	10497	12108	9169	9169
R-squared	0.41	0.29	0.29	0.42	0.46	0.46	0.44	0.46	0.46
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel C: Predicting Stock Return

	(1) t+1	(2) t+1	(3) t+1	(4) t+2	(5) t+2	(6) t+2	(7) t+3	(8) t+3	(9) t+3
Inside view E	-0.01	-0.01	-0.01	0.00	-0.00	-0.00	-0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inside view S	-0.00	-0.00	-0.01	0.00	-0.00	-0.01	0.02**	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inside view G	0.04***	0.02**	0.01*	0.03***	0.02***	0.02**	0.03***	0.01*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MSCI E		0.00	0.00		-0.00	-0.00		0.00	0.00
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
MSCI S		0.02**	0.02**		0.02**	0.01*		0.01*	0.01
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
MSCI G		-0.00	-0.00		-0.01	-0.01		0.01	0.01
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
Overall rating			0.02**			0.03***			0.03***
			(0.01)			(0.01)			(0.01)
Observations	15414	10623	10623	13776	10497	10497	12108	9169	9169
R-squared	0.14	0.19	0.19	0.14	0.16	0.17	0.14	0.17	0.17
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 8: Do employees view ESG practices to improve after the Business Roundtable

In this table, I present coefficient estimates from cross-sectional regressions in which the dependent variable is the change in employees' view of E, S, or G practices between 2018 and 2020, i.e., before and after a firm signed the Business Roundtable's new statement that emphasizes a corporation's purpose is to serve all stakeholders rather than just shareholders. The explanatory variables are *BRT*, an indicator for whether a firm signed the Business Roundtable's statement in 2019, and firm characteristics as controls, including size (log of total assets), market-to-book ratio of assets (Tobin's Q), ROA, leverage, and sales growth, all measured in 2018. All regressions include Fama-French 48 industry fixed effects. In some specifications, I allow the *BRT* indicator to interact with indicators of whether a firm has above-sample-median institutional ownership, analyst coverage, organizational complexity, or advertising intensity during 2014-2018. In Panel A, I show the results for the full sample. In Panel B, I perform the same regression for different subsamples: samples of firms with a high or low (above or not above median) E, S, or G inside view in 2018. Robust standard errors, clustered at the industry level, are reported in parentheses.

Panel A: Change in ESG inside view – full sample.

	(1) E	(2) S	(3) G	(4) E	(5) S	(6) G
BRT	-0.12	-0.04	0.01	1.19***	0.75**	0.08
	(0.17)	(0.12)	(0.11)	(0.31)	(0.30)	(0.25)
BRT x High institutional ownership				0.22	0.06	0.01
				(0.29)	(0.29)	(0.23)
BRT x High analyst coverage				-0.09	-0.56	0.16
				(0.32)	(0.40)	(0.33)
BRT x High complexity				-1.30***	-0.41	-0.22
				(0.26)	(0.49)	(0.34)
BRT x High advertising intensity				-0.17	0.36	0.01
				(0.29)	(0.30)	(0.26)
BRT x High COVID exposure				0.16	-0.12	0.18
				(0.30)	(0.39)	(0.23)
Observations	1022	1022	1022	880	880	880
R-squared	0.07	0.04	0.06	0.08	0.06	0.07
Controls	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Panel B: Change in ESG inside view – sub-sample by prior ESG inside view.

	(1) High E	(2) Low E	(3) High S	(4) Low S	(5) High G	(6) Low G
BRT	0.02	-0.40	0.19	0.01	0.06	0.05
	(0.19)	(0.24)	(0.21)	(0.14)	(0.13)	(0.14)
Observations	665	349	300	713	452	565
R-squared	0.23	0.17	0.17	0.07	0.10	0.14
Controls	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 9: Do employees view ESG practices to improve after firms join the UN Compact?

In this table, I present coefficient estimates from regressions in which the dependent variable is the change in the average E, S, or G inside view 3 years before to 3 years after a firm joins the UN Global Compact. The main explanatory variable is an indicator (*UNGC*) equaling one for firms that join the UN Global Compact, and zero for control firms. In some specifications, I allow the *UNGC* indicator to interact with indicators of whether a firm has a high average institutional ownership, analyst coverage, organizational complexity, or advertising intensity in the three years before joining the UNGC. I select up to 10 control firms for each firm that ever joins the UNGC based on the propensity score estimated using a logit model with the following covariates: lagged ESG inside views and other firm characteristics (size, ROA, leverage, sales growth, Tobin's Q, and institutional ownership). I require that control firms belong to the same year and Fama-French 48 industry classification with the UNGC firm and that the gap between the propensity score of the UNGC firm and that of any control firm be smaller than 0.1 (i.e., caliper is 0.1). If a firm is selected as a control firm in multiple years, I keep only the first year as a pseudo-treatment year for that control firm. All regressions include Fama-French 48 industry fixed effects. Control variables, when included, are size, ROA, leverage, sales growth, Tobin's Q, and institutional ownership. In Panel A, I show the results for the full sample. In Panel B, I perform the same regression for different subsamples: samples of firms with a high or low (above or not above median) E, S, or G view by employees before a firm joins the UNGC. Robust standard errors, clustered at the industry level, are reported in parentheses.

Panel A: Change in ESG inside view – full-sample.

	(1) E	(2) S	(3) G	(4) E	(5) S	(6) G	(7) E	(8) S	(9) G
UNGC	-0.20	0.17***	0.20*	-0.19	0.11*	0.17	-0.37	0.14	0.66*
	(0.13)	(0.05)	(0.10)	(0.13)	(0.06)	(0.10)	(0.27)	(0.20)	(0.33)
x High inst. ownership							0.08	-0.11	-0.41**
							(0.19)	(0.17)	(0.18)
x High analyst coverage							-0.14	-0.06	-0.21
							(0.29)	(0.12)	(0.23)
x High complexity							0.30	-0.11	-0.21
							(0.32)	(0.11)	(0.22)
x High advertising intensity							0.06	0.26*	-0.07
							(0.18)	(0.13)	(0.15)
Observations	632	632	632	632	632	632	632	632	632
R-squared	0.07	0.10	0.10	0.08	0.13	0.14	0.08	0.14	0.16
Controls	no	no	no	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes	yes	yes	yes

Panel B: Change in ESG inside view – sub-sample by prior ESG inside view.

	(1) High E	(2) Low E	(3) High S	(4) Low S	(5) High G	(6) Low G
UNGC	-0.15	-0.20	0.29***	-0.09	0.09	0.21*
	(0.14)	(0.16)	(0.09)	(0.06)	(0.15)	(0.11)
Observations	232	397	290	342	286	344
R-squared	0.24	0.20	0.30	0.20	0.30	0.18
Controls	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 10: Do employees view ESG practices to improve after a court ruling?

This table examines how the employees' inside view of E, S, and G practices (Panel A) and performance metrics (Panel B) changed in firms headquartered in the states covered by the Seventh Circuit Court (treated firms) relative to other US firms (control firms) around the court ruling in July 2013 that increased the risk of discrimination lawsuits for the treated firms, as described in Section 5. I restrict the sample to firm-years with at least 10 reviews. The results are similar with a higher cutoff like 15, 20, or 28 (sample median) reviews. Here, I regress the inside view on different ESG categories on the interactions between the *Treat* indicator (for treated firms) and different time indicators: *Post(t)* for the year 2013, *Post(t+1)* for the year 2014, *Post(t+2)* for the year 2015, and *Post(t+3)* for the years 2016 onwards. I also test for pre-trends by interacting the *Treat* indicator with indicators for the years before 2013: *Pre(t-2)* to *Pre(t-3)*. The indicator for the year t-1, or 2012, is omitted because 2012 is chosen as the reference year for the related regressions. The indicator *Post* without a time subscript equals one for any years since 2013 and zero for the years before that. All regressions include a constant, firm fixed effects, and year fixed effects. Detailed variable definitions are in the Internet Appendix. Standard errors, clustered at the state level, are reported in parentheses.

Panel A: The inside views after the court ruling

	(1) E	(2) E	(3) E	(4) S	(5) S	(6) S	(7) G	(8) G	(9) G
Treat * Post	-0.02			0.09***			-0.06		
	(0.03)			(0.03)			(0.07)		
Treat * Post (t)		0.07	0.10		0.21***	0.18***		-0.24***	-0.31***
		(0.05)	(0.11)		(0.07)	(0.05)		(0.07)	(0.08)
Treat * Post (t+1)		0.02	0.05		0.05	0.02		0.05	-0.01
		(0.04)	(0.10)		(0.08)	(0.06)		(0.06)	(0.07)
Treat * Post (t+2)		-0.13	-0.10		0.12***	0.09***		-0.09	-0.15*
		(0.10)	(0.06)		(0.03)	(0.03)		(0.08)	(0.08)
Treat * Post (t+3)		-0.03	-0.00		0.06*	0.03		-0.04	-0.11
		(0.04)	(0.06)		(0.04)	(0.05)		(0.07)	(0.08)
Treat * Pre (t-3)			0.05			-0.05			-0.11
			(0.11)			(0.08)			(0.07)
Treat * Pre (t-2)			0.03			-0.05			-0.08
			(0.08)			(0.06)			(0.06)
Observations	16353	16353	16353	16353	16353	16353	16353	16353	16353
R-squared	0.21	0.21	0.21	0.29	0.29	0.29	0.41	0.41	0.41
Controls	No	No	No	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Panel B: Financial performance after the court ruling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Tobin's Q			Sales growth			Return on assets	
Treat * Post	-0.06			0.00			0.01		
	(0.05)			(0.06)			(0.03)		
Treat * Post (t)		-0.03	-0.02		0.02	0.07		0.02	0.01
		(0.05)	(0.04)		(0.07)	(0.06)		(0.03)	(0.05)
Treat * Post (t+1)		-0.07*	-0.06*		-0.08	-0.02		0.01	-0.00
		(0.04)	(0.04)		(0.05)	(0.07)		(0.04)	(0.05)
Treat * Post (t+2)		-0.08	-0.08**		-0.01	0.04		0.00	-0.01
		(0.06)	(0.04)		(0.06)	(0.08)		(0.04)	(0.04)
Treat * Post (t+3)		-0.07	-0.06		0.02	0.07		0.00	-0.01
		(0.06)	(0.05)		(0.07)	(0.08)		(0.04)	(0.05)
Treat * Pre (t-3)			-0.00			0.04			-0.02
			(0.04)			(0.08)			(0.07)
Treat * Pre (t-2)			0.05			0.16*			-0.01
			(0.06)			(0.10)			(0.03)
Observations	0.04***	0.04***	0.04***	-0.00	-0.00	-0.01	0.00	0.00	0.00
R-squared	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Controls	No	No	No	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

INTERNET APPENDIX

IA1: Sample construction and merging across datasets.

I start with the list of 7,851 US-headquartered companies with at least 100 reviews on Glassdoor as of July 2020. For each firm on Glassdoor, there is a unique Glassdoor ID. Firms' tickers and names help me match these unique Glassdoor IDs to other databases. I then match these Glassdoor IDs to the companies available on Compustat during 2008-2020 using stock tickers, when available, and company names. There are 1,780 firms with a unique stock ticker in the Glassdoor dataset. For firms without a unique stock ticker, I conduct fuzzy matching based on names using the *matchit* package in Stata. To improve matching quality, I remove common string patterns, such as Inc., Co., Limited, … I manually verify the matches and keep only the matches with above 95% similarity. Matching on names, however, sometimes creates multiple CUSIP matches for each Glassdoor ID in some year. In these cases (below 70 observations), I keep only the CUSIP for which the associated firm has the highest total asset.

Similarly, I match my firm-year data with the MSCI KLD dataset using tickers and names. Around 70% of US firms in the MSCI dataset during 2008-2018 have a unique ticker. For these firms, I exact-match them with firms in my Glassdoor-Compustat dataset. For the other 30% of firms and firms that cannot be matched to a Glassdoor firm based on ticker, I conduct a fuzzy match based on names using the *matchit* package in Stata. To improve matching quality, I remove common string patterns among company names, such as Corp., Inc., Co., Limited, Holdings…I manually verify the matches and decide to keep only the matches with above 89% similarity. I allow for a smaller cutoff here because manual inspection of the matches reveals that the matching quality is still high up to that cutoff point.

IA2: Variable description

This table shows detailed description for variables used in my analyses. All variables are at the firm-year level. All scaled variables are winsorized at the 1st and 99th percentiles.

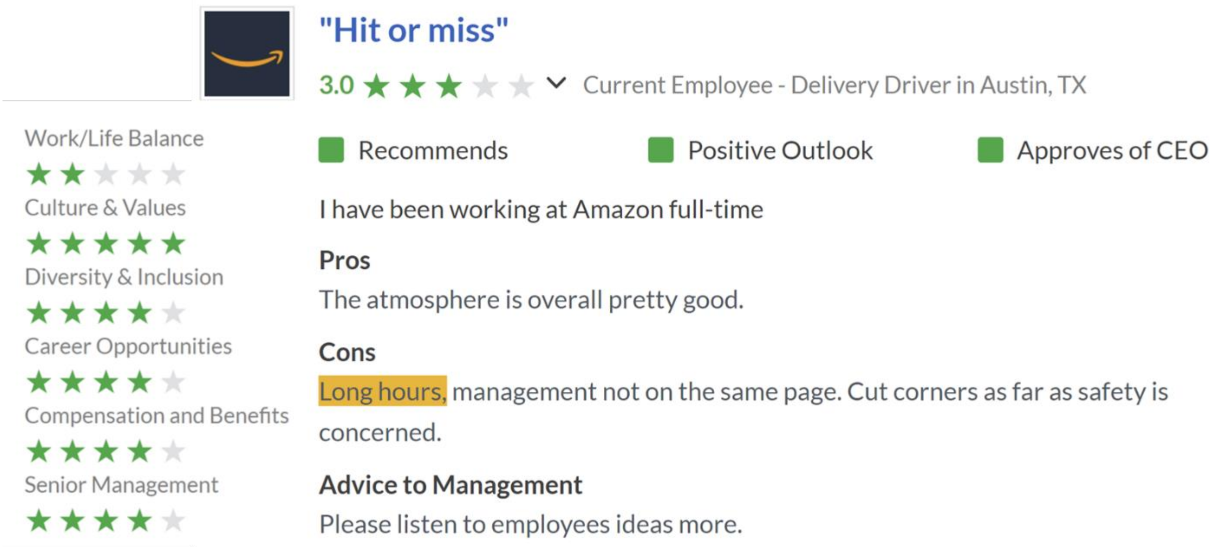
Variable	Definition	Source
No. of reviews	The number of reviews per firm-year	Glassdoor
Inside view (E, S, or G)	At the review level, it is the percentage of environmental, social, or governance key words in the pros section minus the percentage of environmental, social, or governance key words in the cons section in the review, respectively; Averaging this measure across all reviews in a firm-year gives the inside view (E, S, or G) at the firm-year level.	Glassdoor
MSCI (rating E, S, or G)	The number of environmental (E), social (S), or governance (G) strengths minus the number of E, S, or G concerns per firm-year, scaled by the sum of strengths and concerns per category. When no strengths or concerns are recorded, the measure is set to zero if the firm has a record in the MSCI database that year, but set to missing otherwise.	MSCI (KLD)
BRT	An indicator equaling 1 for firms whose CEOs signed the Business Roundtable statement in 2019	BRT website
UNGC	An indicator equaling 1 for firm-years during which a firm is a member of the UN Global Compact	UNGC website
Scope 3 emission disclosure	An indicator equaling 1 if a firm discloses Scope 3 carbon emissions in a year	Asset4 (Refinitiv)
Log(total emissions)	Logarithm of a firm's total disclosed carbon emissions in a year, including Scope 1, Scope 2, and Scope 3 emissions.	Asset4 (Refinitiv)
Fortune Best Companies indicator	An indicator equaling one if a firm belongs to Fortune's Best 100 Companies to Work For in a year	Alex Edman's website
Best Diversity indicator	Indicator equaling one for firms on the Best Companies for Diversity list in different years, zero otherwise.	Fortune Magazine
Number of IC weaknesses	The number of internal control weaknesses a firm's auditor reports about the firm in a year.	Audit Analytics
Number of IC weaknesses	The number of internal control weaknesses reported by a firm's auditor in a year	Audit Analytics
Misstatement risk	the probability of the firm's having a material accounting error in a year, estimated from its accounting numbers and market conditions in that year using a machine learning model as in Bertomeu et al. (2021)	Bertomeu et al. (2021)'s website
Number of shareholder activism filings	The number of Forms 13D filed with a firm in a year for which Audit Analytics classifies as concern, dispute, control, or discussion (following Klein and Zur (2009), Guo et al. (2021))	Audit Analytics
Yearly buy-and-hold return	Stock return for a firm during a calendar year.	CRSP
Downside volatility	The standard deviation of daily returns that are negative in year for a firm's stock	CRSP
Tail risk	The average absolute value of the 5% lowest daily returns in a year for a firm's stock	CRSP

Variable	Definition	Source
Size (log assets)	Logarithm of a firm's total assets in millions, the latest accounting number available in a year	Compustat
Tobin's Q	(total assets + market value of equity − total common equity − deferred taxes)/total assets; or (at-ceq-txditc+mkvalt)/at	Compustat
ROA (return on assets)	EBITDA/lagged assets	Compustat
Leverage	Total liabilities over total assets; or lt/at	Compustat
R&D	Research and Development expense (xrd) over total assets, and zero if missing xrd.	Compustat
Sale growth	The change in the logarithm of a firm's net sales in a year relative to its lag	Compustat
Institutional Ownership	The sum of dollar value of institutional ownership, divided by the sum of market value across securities per firm-year	Thomson Reuters 13F
High institutional ownership	An indicator equaling one if a firm has an above-sample-median institutional ownership in a year and zero otherwise.	Thomson Reuters 13F
High analyst coverage	An indicator equaling one if a firm has an above-sample-median analyst coverage in a year and zero otherwise; where analyst coverage is the number of unique analysts making at least one earnings forecast for the firm in that year.	I/B/E/S
High complexity	An indicator equaling one if a firm has an above-sample-median complexity score in a year and zero otherwise; where the complexity score is the first factor in a factor analysis of business segments, natural logarithm of sales, and leverage (see Coles, Daniel, and Naveen, 2008).	Compustat; Compustat Segments
High advertising intensity	An indicator equaling one if a firm has an above-sample-median advertising over sales in a year and zero otherwise; firm-years with missing advertising data is assumed to have zero advertising.	Compustat
High COVID exposure	An indicator equaling one if a firm belongs to a NAICS-3-digit industry with a COVID exposure score above median across industries; where the COVID exposure score is the communication_interact_share score provided by Koren and Peto (2020).	Koren and Peto (2020)

IA3: Glassdoor review data

This appendix has two panels. Panel A shows an example of a Glassdoor review. Panel B shows the types of employers with at least one review on Glassdoor as of July 25, 2020.

Panel A: example review of Amazon



Panel B: Types of employers reviewed on Glassdoor

	At least 1 review	At least 10 reviews
Company - Private	197,992	58,834
Company - Public	31,131	9,804
Nonprofit	19,853	6,221
Subsidiary/Segment	8,205	4,835
Government	7,235	2,560
Private Practice	6,508	1,088
School	5,592	1,271
College	3,790	2,629
Contract	3,464	594
Franchise	3,020	852
Hospital	2,614	1,253
Self-employed	1,127	88
Other Organization	4,470	829
Unknown	6,550	1,105
Total	**301,551**	**91,963**

IA4: Training the word2vec model.

Before feeding the reviews into the word2vec model, I apply several preprocessing steps to clean the raw reviews. First, I convert each review into its lower-case form and remove all punctuations. Second, I convert each review into a list of individual words. Third, I apply lemmatization on each word, a common practice in natural language processing to convert each word into its standard dictionary form. Fourth, I use the Python package *Spacy* to remove from all reviews any digits and stop words, such as a, an, the, too, all…, which do not convey much meaning. Finally, I identify commonly used two-word phrases (bigrams) in my reviews using the *Phraser* module of the *Genism* library in Python. For each two-word phrase, I concatenate the two words and treat them as a single word and only retain a phrase in my corpus if it appears at least 50 times in all reviews. All these steps follow Li et al. (2021) except that I only model bigrams instead of trigrams to reduce computational costs.

Next, I train the word2vec model by employing all the 10.4 million English reviews available in my data. Each review contains a pro section and a con section, so my input into the word2vec model includes 20.8 million units of text. I follow all the default settings of word2vec in training my model, except that I set the vector size to be 300 and the number of iterations over the training data (epochs) to be 20 as in Li et al. (2021).

Besides using the word2vec model to find words that are most similar to ESG categories, I use the model to classify employees into high-ranked and low-ranked employees in one robustness test. Specifically, I classify employees who write a review into high and low ranks based on their titles. I do so by comparing how similar an employee's title is to a list of high-ranked job titles relative to a list of low-ranked job titles, both are from Glassdoor's official guide to the hierarchy of job titles, available at https://www.glassdoor.com/blog/guide/hierarchy-of-job-titles/. I group C-suite titles and manager titles into the high-ranked list, and individual contributors and entry-level titles into the low-ranked list. I then transform each title into bigrams or unigrams and only keep those that are in my word2vec model's vocabulary. Then, I calculate the average vector representing all the remaining words in each list. I then compare the two vectors representing the low-ranked and the high-ranked job titles to the average vector representing words in an employee title to decide if the employee title indicates a high-ranked employee. If an employee' title is anonymous or unknown, I deem the employee to be low-ranked.

I find that 17% of reviews were written by a high-ranked employee. Removing these reviews changes the inside view measure little, with the resulting measure having a correlation of above 0.93 with the baseline measure.

IA5: Employees' attention to ESG issues over time.

Given the recent rise in ESG investing, employees are likely to mention ESG catchphrases more over time. Figure IA1a shows that to be the case. The frequency of *ESG, CSR*, *sustainable*, and *sustainability*, while small, has increased significantly between 2008 and 2021. The word *ESG* alone did not even appear in employee reviews until 2015.

However, employees' attention to ESG issues more broadly, as captured by my comprehensive ESG dictionaries, might not show an increasing trend over time. A firm's employees are likely to have always cared about many ESG issues like employee treatment and business ethics, regardless of whether the firm's investors care about these issues. Indeed, Figure IA1b shows that the overall attention to ESG issues by employees has remained rather stable over time. One alternative explanation could be that my ESG dictionaries over-represent ESG words often used in the earlier period relative to the later period, leading to the flattening of the otherwise increasing trend in the employees' attention to ESG issues. Nonetheless, when I train my model on only reviews in the later period (2015-2021), the resulting ESG dictionaries overlap 94.4% with the baseline dictionaries. By contrast, consistent with the employees' stable attention to ESG issues over time, I find in un-tabulated tests that the employees' inside view predicts future ESG performance indicators in both the earlier and the later sample periods.

Despite its overall flat trend, the employees' attention spiked around major ESG events. The attention to E issues was the highest in 2008 when Barrack Obama, who promised to reform environmental law enforcement, won the U.S. Presidential Election. The attention to E issues was also high in 2015 when world leaders signed the Paris Agreement, an international treaty on climate change. On S issues, the most noticeable spikes were in 2020 when the Global Pandemic first hit the US and again when the death of George Floyd raised massive racial protests in the country. Finally, about governance, the most noticeable spikes were during the 2008 Financial Crisis and 2020 Pandemic when companies' governance was put to the test. In unreported graphs that zoom in at higher frequencies, I find that the ESG attention fits the timing of these ESG events.

IA6: An inside view of a narrower ESG issue: diversity and inclusion.

To measure an inside view of a firm's diversity and inclusion (D&I) practices, I follow all the steps of measuring the inside view of ESG practices, unless stated otherwise. First, I specify the seed words for the D&I topic to include *diversity*, *inclusion*, *discrimination*, *inequality*, and words with the same roots, such as *diverse*, *inclusive*, and *discriminating*. The main results in my paper do not change significantly if I omit *discrimination*, *inequality*, and their related words, or if I keep the seed word lists separately for D&I and discrimination/inequality. Since the seed word list of each ESG topic has 50 words, I expand the D&I seed word list to the 50 most similar words using Google's own word2vec model pretrained on a news dataset.[28] From this expanded seed word list for the D&I topic, I use my word2vec model, trained on 10.4 million employee reviews, to find the top 500 most similar words to be by final dictionary of D&I key words. With the D&I dictionary, I count D&I words in my reviews and average the D&I word frequency in the pros relative to the cons sections across reviews per firm-year to calculate my measure of the D&I inside view.

I find that the rank correlation between the D&I inside view and the D&I ratings from Refinitiv and MSCI to be low, at 0.19 and 0.10, respectively.

[28] https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit?usp=sharing

Figure IA1: Trends in employees' attention to ESG issues

Figure a plots the percentage of ESG catchphrases, namely *ESG*, *CSR*, *sustainable*, and *sustainability*, in an average review from 2008 to 2021. Figure b plots the average attention to E, S, and G issues across reviews for each quarter between 2008 and 2021. Before aggregating to the quarter level, I measure the attention to each ESG category for each review by the percentage of words on each category, from my comprehensive ESG dictionaries, in each review.

Figure IA1a: Attention to ESG catchphrases

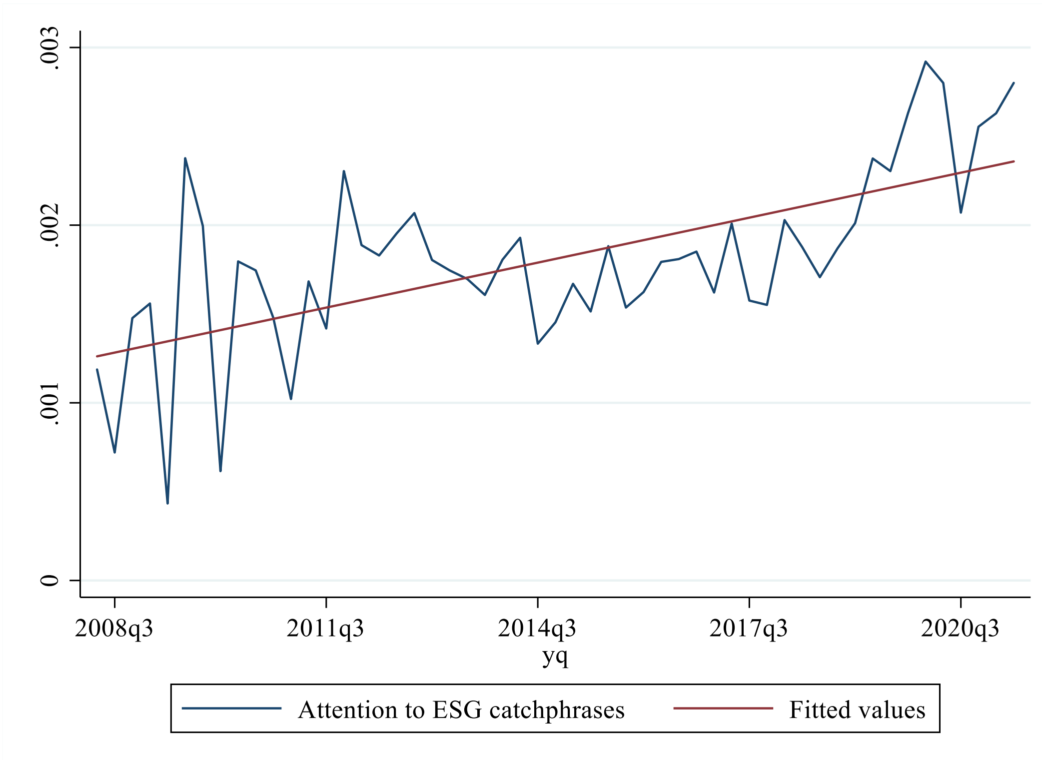


Figure IA1b: Attention to E, S, and G issues more broadly

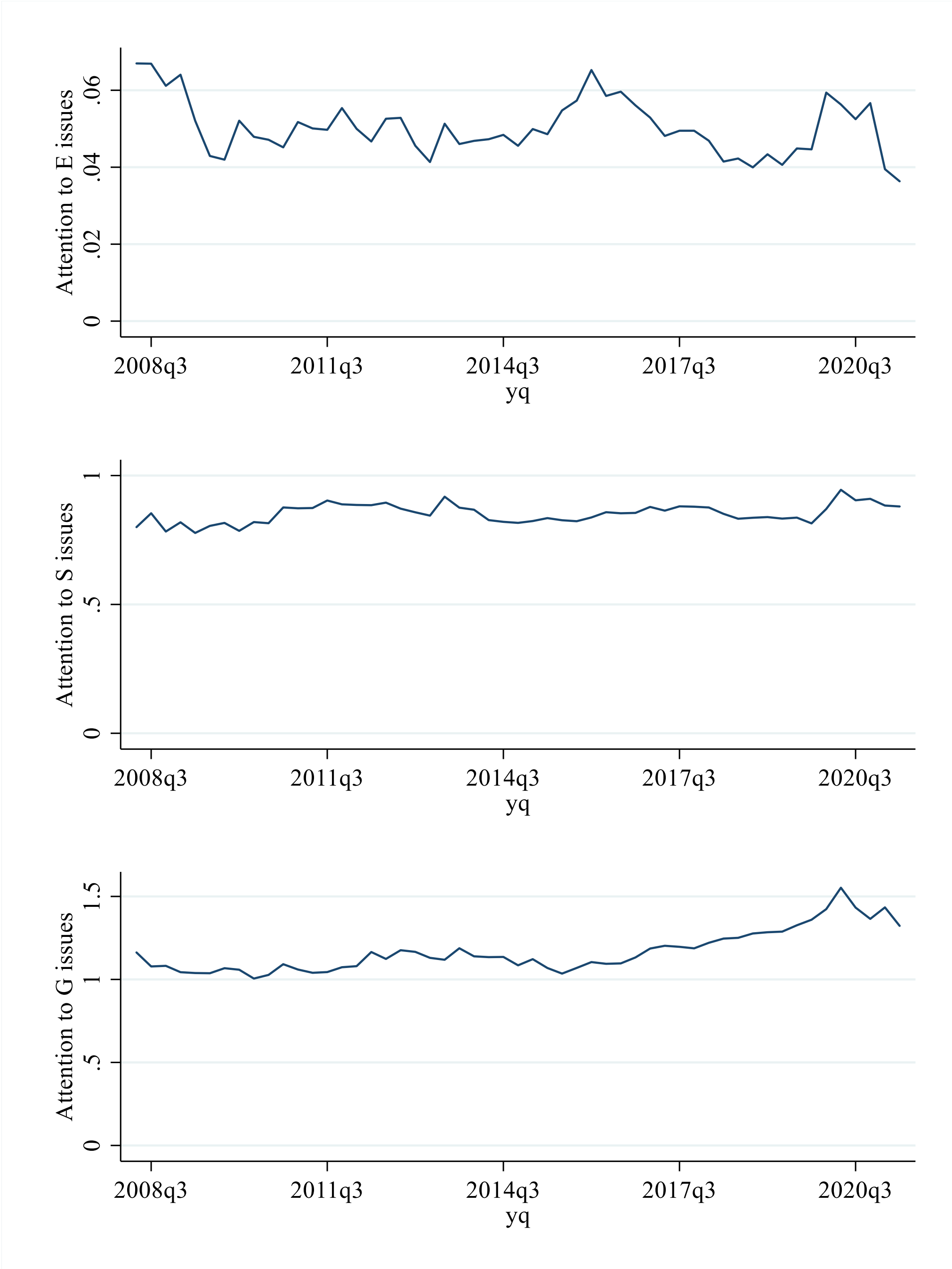


Figure IA2: Trends around the 2013 court ruling on D&I

This figure plots the typical diff-in-diff (difference in differences) graph around the circuit court ruling on diversity and inclusion in 2013. In particular, it plots the regression coefficients (along with the 95% confidence intervals) on the interactions between the treatment indicator (equaling one for firms headquartered in Indiana, Illinois, and Wisconsin, and zero otherwise) and year indicators relative to the treatment year: 2013. The indicator for the year t-1, or 2012, is omitted because 2012 is chosen as the reference year. The dependent variables include the ESG inside views, Tobin's Q, sales growth, and return on assets. All regressions include a constant, firm fixed effects, and year fixed effects. Detailed variable definitions are in the Internet Appendix IA3. The 95% confidence intervals are based on standard errors that are clustered at the state level.

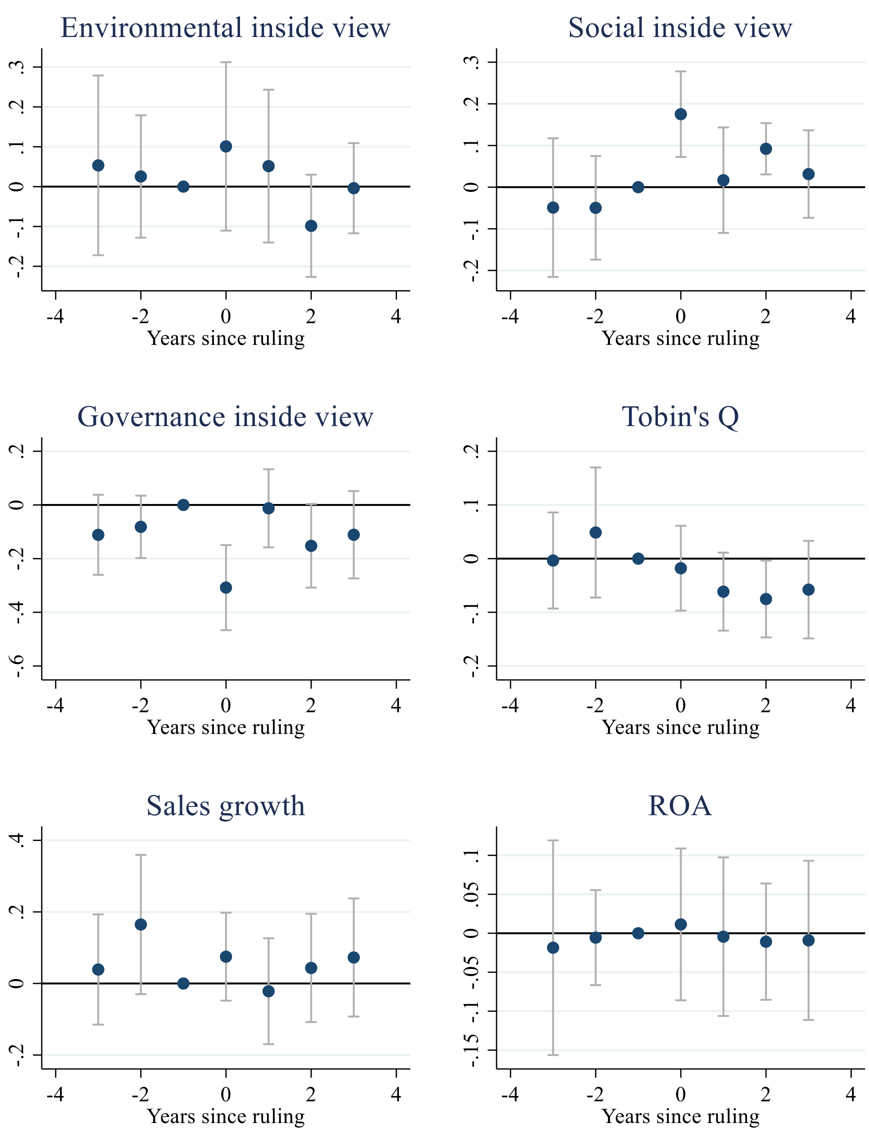


Table IA1: Industry composition of the main sample

This table shows the number and frequency of firms in different industries among my sample of 1,936 unique US publicly listed companies. For comparison, I also report the frequency of different industries in a sample of Compustat firms with a non-missing market value and an average total assets during 2008-2020 that exceeds the minimum average total assets of firms in my sample.

Fama-French industry code	Freq.	My sample Percent	Compustat Percent
Business Services	414	21.38%	11.29%
Retail	151	7.80%	3.23%
Banking	99	5.11%	11.15%
Electronic Equipment	83	4.29%	4.23%
Trading	76	3.93%	6.16%
Computers	70	3.62%	2.20%
Insurance	67	3.46%	2.33%
Wholesale	62	3.20%	2.48%
Restaraunts, Hotels, Motels	56	2.89%	1.29%
Communication	52	2.69%	2.07%
Transportation	52	2.69%	2.59%
Machinery	48	2.48%	1.94%
Healthcare	43	2.22%	1.51%
Pharmaceutical Products	43	2.22%	11.78%
Medical Equipment	38	1.96%	3.13%
Petroleum and Natural Gas	37	1.91%	5.00%
Utilities	35	1.81%	1.53%
Automobiles and Trucks	29	1.50%	1.03%
Food Products	28	1.45%	1.23%
Consumer Goods	28	1.45%	0.84%
Apparel	28	1.45%	0.78%
Chemicals	28	1.45%	1.59%
Personal Services	28	1.45%	0.89%
Measuring and Control Equipment	28	1.45%	1.15%
Construction Materials	25	1.29%	1.19%
Entertainment	23	1.19%	1.26%
Electrical Equipment	20	1.03%	1.21%
Almost Nothing	20	1.03%	5.30%
Construction	19	0.98%	0.88%
Printing and Publishing	15	0.77%	0.38%
Steel Works Etc	14	0.72%	0.72%
Business Supplies	14	0.72%	0.59%
Real Estate	14	0.72%	1.10%
Aircraft	12	0.62%	0.32%
Shipping Containers	9	0.46%	0.15%
Recreation	8	0.41%	0.51%
Rubber and Plastic Products	6	0.31%	0.43%

Defense	6	0.31%	0.13%
Candy & Soda	5	0.26%	0.23%
Beer & Liquor	5	0.26%	0.17%
Non-Metallic and Industrial Metal Mining	4	0.21%	1.44%
Agriculture	3	0.15%	0.31%
Tobacco Products	3	0.15%	0.05%
Textiles	3	0.15%	0.15%
Shipbuilding, Railroad Equipment	3	0.15%	0.16%
Fabricated Products	2	0.10%	0.13%
Coal	2	0.10%	0.35%
Precious Metals	1	0.05%	1.44%
Unclassified	77	3.98%	0.00%
Total	1936	100.00%	100.00%

Table IA2: Lists of ESG issues from industry and academic sources

In this table, Panel A shows the detailed sources where I obtain the lists of ESG issues to create an initial seed word list for each ESG category. Panel B shows the top 25 unigrams and top 25 bigrams that are most frequently used among these sources on each ESG category and also present in the vocabulary of the *word2vec* model trained on 10.4 million employee reviews as described in Section 4. These form the initial seed word lists on ESG topics.

Panel A: Source texts containing lists of ESG issues

Source	Category	Location	Source name	Link
MSCI	E	Page 4	MSCI ESG Ratings Methodology Executive Summary MSCI ESG Research September 2019	https://www.msci.com/documents/1296102/14524248/MSCI+ESG+Ratings+Methodology+-+Exec+Summary+2019.pdf
	S	Page 4		
	G	Page 4		
MSCI	E	Page 18-25	MSCI ESG KLD Stats: 1991-2015 Data Sets	https://libguides.uml.edu/ld.php?content_id=59552417
	S	Page 25-39		
	G	Page 39-41		
Refinitiv	E	Page 10	Environmental, Social and Governance (ESG) Scores from Refinitiv April 2020	https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf
	S	Page 10		
	G	Page 10		
Refinitiv	E	Datastream	Variable Names in Asset4 Dataset	Datastream variable search
	S	Datastream		
	G	Datastream		
S&P Global (RobecoSAM)	E	Figure 4	Measuring Intangibles RobecoSAM's Corporate Sustainability Assessment Methodology	https://www.spglobal.com/spdji/en/documents/additional-material/robeco-sam-measuring-intangibles.pdf
	S	Figure 4		
	G	Figure 4		
S&P Global (RobecoSAM)	E	Page 2-3	CSA Companion 2021 Corporate Sustainability Assessment	https://portal.csa.spglobal.com/survey/documents/CSA_Companion.pdf
	S	Page 3		
	G	Page 3-4		
Sustainalytics	E	All	Descriptions of Material ESG Issues and Corporate Governance	https://www.sustainalytics.com/docs/default-source/meis/definitionsofmeis.pdf?sfvrsn=8e7552c0_4
	S	All		
	G	All		
Vigeo Eiris	E	Page 1	Eiris Sustainability Ratings	https://www.vigeo-eiris.com/wp-content/uploads/2016/11/EIRIS SustainabilityRatings.pdf
	S	Page 1		
	G	Page 1		
Vigeo Eiris	E	Page 5	ESG Assessment Methodology Executive Summary	https://prodtest-01.vigeo-eiris.com/wp-content/uploads/2021/05/VE_ESG-Assessment-Summary_2021.pdf
	S	Page 5		
	G	Page 5		
RepRisk	E	Page 1	RepRisk Research Scope: ESG Issues, August 2020	https://www.reprisk.com/media/pages/static/2738025864-1618582399/reprisk-esg-issues-definitions.pdf
	S	Page 2-3		
	G	Page 3-4		
CSRHub	E	All	CSRHub Data Schema Description	https://esg.csrhub.com/csrhub-esg-data-schema
	S	All		
	G	All		
	E	Table 3		

Source	Category	Location	Source name	Link
Baier, Berninger, and Kiesel (2020)	S	Table 3	Environmental, Social and Governance Reporting In Annual Reports: A Textual Analysis	https://onlinelibrary.wiley.com/doi/full/10.1111/fmii.12132
	G	Table 3		
Bessec and Fouquau (2021)	E	Table 1	Green Sentiment in Financial Markets: A Global Warning, Date Written: October 13, 2020	https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3710489

Panel B: Top 50 words from the source texts on ESG topics

Environmental	Social	Governance
environmental, emission, waste, climate, energy, water, carbon, biodiversity, pollution, change, use, green, resource, impact, risk, material, packaging, renewable, toxic, recycle, footprint, environment, land, disposal, greenhouse, raw material, renewable energy, carbon footprint, oil spill, efficiently effectively, supply chain, east asia, global footprint, global warming, environmental protection, national park, environmental sustainability, drink water, noise pollution, fossil fuel, electric vehicle, solar energy, solar panel, plastic bag, green belt, air pollution, wind turbine, nuclear power, natural gas, fluorescent lighting	human, right, employee, health, safety, labor, community, labour, social, relation, access, development, capital, indicator, child, responsible, philanthropy, training, fundamental, standard, workforce, privacy, citizenship, occupational, employment, human capital, corporate citizenship, occupational health, supply chain, community involvement, race ethnicity, discrimination harassment, turnover rate, medicaid medicare, performance indicator, collective bargaining, human resource, minimum wage, safe secure, working condition, warning letter, age discrimination, gender racial, racial ethnic, unfair dismissal, human trafficking, threat violence, business model, charitable donation, charitable giving	board, governance, shareholder, ethic, practice, corruption, instability, compensation, structure, code, bribery, tax, corporate, committee, executive, esg, transparency, ownership, audit, level, management, independence, diversity, director, business, code conduct, gender diversity, financial instability, board director, insider trading, financial institution, daytoday operation, tax evasion, false advertising, money laundering, cultural diversity, wide spectrum, policy procedure, 3rd party, regulatory scrutiny, track record, unethical behavior, law violation, nepotism cronyism, hold accountable, government agency, stock price, accountable action, notice period, golden parachute

Table IA3: From seed word lists to final ESG dictionaries

These following tables show how the seed word lists change after I remove noisy words from them and finally arrive at the full ESG dictionaries. Panel A shows the seed word lists after I remove noisy words from the initial seed word list for each ESG category (shown in Table IA2 Panel B). I consider a word as noisy if it is outside of the top 1000 words with the highest cosine similarity to the average vector representing the initial seed word list. I also remove *supply chain* from the E category, *fundamental* from the S category, and *financial institution*, *government agency*, and diversity-related words from the G category. Panel B shows how the last twenty words of the full dictionaries would look like with different cutoffs for the dictionaries' size. When a word appears in multiple dictionaries, I only keep it in the category to which it is most similar. Panel C shows the words most commonly used in employee reviews on each ESG category.

Panel A: The seed word lists after removing noisy words.

Environmental	Social	Governance
environmental, emission, energy, water, carbon, biodiversity, pollution, green, packaging, renewable, recycle, footprint, disposal, greenhouse, raw material, renewable energy, carbon footprint, oil spill, global footprint, global warming, environmental protection, environmental sustainability, noise pollution, fossil fuel, electric vehicle, solar energy, solar panel, plastic bag, air pollution, wind turbine, nuclear power, natural gas	human, employee, health, safety, labor, community, labour, social, relation, philanthropy, workforce, citizenship, occupational, human capital, corporate citizenship, occupational health, community involvement, race ethnicity, discrimination harassment, medicaid medicare, collective bargaining, human resource, age discrimination, gender racial, racial ethnic, unfair dismissal, human trafficking, threat violence, charitable donation, charitable giving	board, governance, shareholder, ethic, practice, corruption, instability, bribery, committee, executive, transparency, ownership, audit, level, diversity, business, code conduct, board director, insider trading, daytoday operation, tax evasion, money laundering, policy procedure, regulatory scrutiny, track record, unethical behavior, law violation, nepotism cronyism

Panel B: Comparing different cutoffs for the final ESG dictionaries' size.

	Environmental	Social	Governance
Last in top 250	gmos, refining, biomaterial, hazardous chemical, nozzle, residential commercial, basin, octg, manufacturing, flour, algae, environmentalism, toxin, masonry, bakken, sawdust, nuclear plant, alloy, sewage, aerial	aapi, assualt, employee, legislation, regulatory compliance, whistleblower, underrepresented, bisexual, minoritys, code conduct, hse, latinos, political correctness, grantmake, health, homosexual, tokenism, christianity, spiritual, trauma inform	widespread, oversight, identity, greed, bullying, belief, ineptness, funder, government official, illegal immoral, sarbanesoxley, credibility, fbi, demonstrate, predatory lending, human capital, discriminatory behavior, intent, disclosure, ethos
Last in top 500	actuator, sediment, consol, rtus, faucet, carbide, sensor, moulding, jug, conveyor, roofing, kiln, dpf, aerospace, welding, bicycle, ubiquitin, sprinkler, corrugate, environmentalist	bipartisan, maltreatment, organizer, identity theft, exceptionalism, physical assault, red cross, civic, federally, disabled veteran, underprivileged, foreign national, blm movement, oppression, collective bargaining, willful, diverstiy, appropriation, nonreligious, heart disease	advisory, dishonorable, credo, elitism, egotism, white supremacy, organizational structure, citizenship, lobbyist, competency, procurement, cabal, ethically morally, influence, executivelevel, thereof, usaid, stem, hiringpromotion, unethicalimmoral
Last in top 1000	importer, leed certify, haz, kazakhstan, pollute, agri, opex, dehydration, txu, eprocurement, audio visual, next generation, inhabitant, flashlight, smallholder, microprocessor, manufature, hazardous, busted, computing	donation charity, watchdog, east asian, americorps member, clergy, somali, white savior, coercion, irc, hremployee, honesty integrity, nondisclosure agreement, polarization, reentry, envolvement, palliative, soldier, children, performative, closeted	inner working, obsession, backbone, boli, merger acquisition, lie deception, founder syndrome, pcaob, ousting, 501c3, pennypinching, tokenism, nonperformance, antibullye, non compliant, rampant sexism, antiharassment, disinterest, commonsense, border

Panel C: Most frequently used ESG key words in employee reviews.

Environmental	Social	Governance
plant, water, construction, manufacturing, green, manufacture, oil, industrial, environmental, oil gas, planet, storage, chemical, manufacturer, utility, solar, engine, footprint, electrical, recycle, lighting, electric, plastic, steel, packaging, battery, metal, mining, pipe, nuclear	employee, health, community, workplace, diversity, safety, social, workforce, human, personnel, human resource, legal, cultural, mental health, discrimination, welfare, harassment, population, wellbeing, minority, regulation, advocate, diversity inclusion, youth, sexual harassment, wellbeing, evidence, racism, society, discriminate	culture, business, leadership, organization, CEO, leader, decision, executive, practice, strategy, operation, financial, ethic, innovation, partner, transparency, initiative, organization, ownership, administration, accountability, action, board, behavior, integrity, engagement, appear, president, professionalism, nepotism

Table IA4: Persistence in the ESG inside view

This table shows the regressions at the firm-year level of the inside view at year t on its value at year t-1, for the E, S, and G categories separately. Control variables, when included, are the numerical ratings on Glassdoor, all averaged across reviews to the firm-year level, measured at year t. Industry fixed effects are based on the Fama French 48 industry classification. Detailed variable descriptions are in Appendix B in the main paper. Robust standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	E inside view		S inside view		G inside view	
Lagged E inside view	0.108***	0.100***				
	(0.014)	(0.015)				
Lagged S inside view			0.138***	0.098***		
			(0.009)	(0.010)		
Lagged G inside view					0.234***	0.135***
					(0.009)	(0.010)
Rating - overall		-0.023**		0.027		0.235***
		(0.011)		(0.050)		(0.067)
Rating - balance		-0.011		0.030		-0.239***
		(0.007)		(0.026)		(0.036)
Rating - culture		-0.005		0.417***		0.464***
		(0.009)		(0.039)		(0.049)
Rating - career		0.023**		-0.115***		0.002
		(0.009)		(0.039)		(0.049)
Rating - compensation		-0.010*		0.108***		-0.265***
		(0.006)		(0.023)		(0.031)
Rating - management		0.006		-0.062		0.629***
		(0.010)		(0.041)		(0.056)
_cons	0.004**	0.021	0.170***	-1.433***	0.114***	-2.526***
	(0.002)	(0.058)	(0.007)	(0.219)	(0.009)	(0.234)
Observations	19740	16295	19740	16295	19740	16295
R-squared	0.012	0.042	0.021	0.120	0.056	0.276
Industry FE	no	yes	no	yes	no	yes

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*