Female Equity Analysts and Corporate Environmental and Social Performance*

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This version: June 2024

Abstract

This paper investigates the impact of female analyst coverage on firms' environmental and social (E&S) performance. Exploiting broker closures as a quasi-exogenous shock to female analyst coverage, we show that firms experiencing an exogenous drop in female analyst coverage subsequently suffer a 7% decline in E&S scores and a deterioration in real E&S outcomes. To uncover the mechanisms, we develop novel machine learning models to analyze a large corpus of over 2.4 million analyst reports and 120,000 earnings call transcripts. Our analysis reveals that female analysts are more likely to discuss E&S issues in their research reports and during earnings conference calls compared to their male counterparts. Moreover, female analysts are more likely to take actionable steps, such as downgrading stock recommendations and lowering target prices, following negative E&S discussions in their reports. By tracing the path from analyst gender to differences in behaviour and ultimately to covered firms' E&S performance, we find evidence that gender diversity among analysts is a key driver of corporate E&S practices. Our findings highlight the importance of promoting gender diversity in the finance industry and offer novel insights into the role of female analysts in shaping corporate E&S practices.

Keywords: female equity analysts; analyst monitoring; corporate environmental and social performance; corporate governance; FinBERT; analyst reports; earnings conference calls

JEL classification: G24; G30; G40

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Abstract

This paper investigates the impact of female analyst coverage on firms' environmental and social (E&S) performance. Exploiting broker closures as a quasi-exogenous shock to female analyst coverage, we show that firms experiencing an exogenous drop in female analyst coverage subsequently suffer a 7% decline in E&S scores and a deterioration in real E&S outcomes. To uncover the mechanisms, we develop novel machine learning models to analyze a large corpus of over 2.4 million analyst reports and 120,000 earnings call transcripts. Our analysis reveals that female analysts are more likely to discuss E&S issues in their research reports and during earnings conference calls compared to their male counterparts. Moreover, female analysts are more likely to take actionable steps, such as downgrading stock recommendations and lowering target prices, following negative E&S discussions in their reports. By tracing the path from analyst gender to differences in behaviour and ultimately to covered firms' E&S performance, we find evidence that gender diversity among analysts is a key driver of corporate E&S practices. Our findings highlight the importance of promoting gender diversity in the finance industry and offer novel insights into the role of female analysts in shaping corporate E&S practices.

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1. Introduction

In 1982, Maryann Keller stood out as one of the few female equity analysts on Wall Street. She leveraged an unparalleled network and work ethic to become a top auto industry analyst.[1] Yet three decades later, women still remain underrepresented on the sell-side, comprising 11% of equity analysts. The obstacles confronting female analysts have only grown as a fleeting push for greater diversity has given way to a forceful backlash. At bulge bracket banks like Goldman Sachs and Bank of America, once-heralded initiatives to promote female representation are being diluted or dismantled.[2]

This retreat lays bare the fragility of attempts to reshape a Wall Street culture long inimical to female advancement and values. A growing literature documents how male-oriented professional networks and promotion dynamics can hinder the careers of women in finance (Fang and Huang 2017; Sherman and Tookes 2022). Female analysts appear particularly vulnerable to these headwinds given both the heavily quantitative skillset and "all in" availability the role has historically demanded. More fundamentally, the qualities that have been shown to contribute to female success in the boardroom, such as universalism and benevolence (Adams and Funk 2012), may be intrinsically at odds with a sell-side research model that prizes short-term forecasting prowess above all else (Kumar 2010). This raises a question – is there ever a point of gender diversity in equity research?

We propose that the answer lies in the rising importance of environmental, social, and governance (ESG) values. In her presidential address, Starks (2023) highlights that ESG values – considering environmental and social (E&S) issues for their financial materiality – can be particularly important for long-term investors. By staying attuned to ESG risks and opportunities, analysts exert pressure on companies to navigate shifting regulatory

[1] See The Atlantic.
[2] See Bloomberg.

landscapes, avoid penalties, and position these companies for enduring success. If female analysts' universalism and benevolence translate into a heightened focus on E&S values with real-world consequences, their distinct perspectives may prove increasingly essential in bridging the gap between shareholder value and nonpecuniary values. Our inquiry is important for two reasons.

To begin with, it is important to test *whether* female analysts' emphasis on the well-being of others, the community, and the environment (Beutel and Marini 1995; Schwartz and Rubel 2005; Bertrand 2011) translates into tangible impacts on the companies they cover. For gender diversity among analysts to meaningfully advance corporate sustainability goals, female analysts' priorities would result in improved E&S performance and outcomes for their covered firms. Moreover, prior studies have not directly observed *how* gender differences manifest in finance professionals' real-world behaviours. Tracing the path from gender to differences in on-the-job conduct and ultimately to covered firms' E&S performance is crucial for validating a core premise underlying gender diversity initiatives: that these efforts can drive change in the finance industry by shaping the practices of its professionals. This link, therefore, serves as the bedrock upon which the credibility of these diversity initiatives rests.

In this paper, we leverage a unique large data set of analyst research activities to explore whether and how female analyst coverage shapes corporate E&S performance. We curate a hand-collected sample of over 10,000 sell-side equity analysts with gender data and different E&S measures over the period 2005–2021. We then match the data set with two large text corpora that reflect analysts' main research activities: over 2.4 million analyst reports and 120,000 earnings call transcripts. Our empirical strategy proceeds in several steps.

First, we show that there is a positive and significant association between the number of female analysts covering a firm and that firm's E&S performance. For identification, we exploit brokerage closures as a quasi-exogenous shock to female analyst coverage. Following a closure, firms losing female analysts experience significant declines in E&S ratings and real E&S outcomes relative to unaffected peers, suggesting a causal impact. Importantly, we confirm that female analysts' impact extends beyond E&S ratings to real outcome measures. An exogenous drop in female equity analyst coverage leads to increased carbon emissions and more workplace safety-related violations. In terms of economic significance, losing one female equity analyst leads to a 7.3% drop in the focal firm's E&S score, approximately 8,800 additional metric tons of CO_2 emissions, $15,000 in additional workplace-related penalties, and one additional workplace-related case.

Next, we turn to analysts' research activities – writing research reports and attending earnings conference calls (Chen, Harford, and Lin 2015). We employ machine learning tools to detect discussions of E&S topics in analyst reports and earnings call transcripts. Given that E&S-related discussions tend to encompass a broad range of topics and linguistic expressions, conventional keyword-based textual analysis methods are inadequate. We develop a new active learning approach to efficiently search for and annotate E&S-related discussions from the large corpora. We then fine-tune the FinBERT model (Huang, Wang, and Yang 2023), a state-of-the-art large language model trained on financial text, to create two tailored E&S text classification models that capture analysts' writing (in analyst reports) and raising questions (during earnings calls) about E&S issues.

We find substantial divergence in the intensity and thematic content of female versus male analysts' E&S commentary. Female analysts discuss E&S topics more frequently and emphasize sustainability-relevant themes like stakeholder welfare, while male analysts focus more narrowly on financial considerations. The results suggest that female analysts actively monitor E&S performance by "voice." Further, we find that female analysts complement their "voice" with "action." Compared to male analysts, female analysts are more likely to downgrade stocks and project lower target prices following negative E&S discussions in their reports. Moreover, investors react significantly to female analysts' negative tones when discussing a firm's E&S performance in their reports. We also establish positive associations between E&S-related discussions in analyst reports or questions during calls, and corporate E&S performance. Importantly, we show that such positive associations are more pronounced for firms with more female analysts following. Finally, we find that female analysts' E&S monitoring does not help them to achieve better career outcomes, including forecast accuracy and All-star status, suggesting career incentives are not a main driver for female analysts monitoring corporate E&S practices.

Our main findings remain in a battery of robust tests. We show that our results are not driven by choices of E&S data providers, measurement of female coverage (using alternative measures such as female coverage ratio), analyst characteristics (such as experience and education), broker size and culture, and firm characteristics (such as ownership by socially responsible investment (SRI) funds). Moreover, we note that the presence of female directors or executives does not affect the positive association. Finally, we show that any change in a firm's female analyst coverage does not lead to immediate changes in a firm's E&S performance, but rather starts to show an effect from the second or third year.

We conclude that female equity analysts play a unique monitoring role in enhancing corporate E&S performance. This monitoring function is distinct from the general governance role served by analysts (see, for example, Yu 2008; Chen, Harford, and Lin 2015) and carries important implications. For example, investors and asset managers could consider gender diversity of sell-side coverage as a relevant indicator of firms' E&S outlook. More broadly, our work highlights gender diversity in equity research as a potential driver of the

ESG agenda with real economic and social consequences – a compelling proof point in how gendered values translate to shareholder value in the "value versus values" debate (Starks 2023).

Our paper makes two contributions to the literature. First, our study contributes to the literature on gender and finance. A growing body of literature has examined how gender diversity in corporate leadership positions, such as the board of directors and the executive suite, can shape firm policies and outcomes (see, for example, Huang and Kisgen 2013; Matsa and Miller 2013; Levi, Li, and Zhang 2014; Tate and Yang 2015; Faccio, Marchica, and Mura 2016; Lai, Srinidhi, Gul, and Tsui 2017; Hsu, Li, and Pan 2023). Prior research has also explored the role of gender among key capital market participants, such as mutual fund managers, hedge fund managers, and sell-side analysts, and has primarily focused on individual performance rather than firm-level effects (see, for example, Kumar 2010; Aggarwal and Boyson 2016; Fang and Huang 2017; Niessen-Ruenzi and Ruenzi 2019). We extend the literature by investigating the impact of gender diversity among sell-side equity analysts, who serve as crucial information intermediaries between firms and investors, on an important dimension of corporate outcomes: E&S practices.

Second, our study contributes to the analyst literature, specifically the strand of the literature on the governance role of analysts (Yu 2008; Irani and Oesch 2013; Chen, Harford, and Lin 2015; Guo, Pérez-Castrillo, and Toldrà-Simats 2019; Bradley, Mao, and Zhang 2022) and on managerial learning from analysts' insights (e.g., Anantharaman and Zhang 2011; Mola, Rau, and Khorana 2013; Guo and Zhong 2023). We extend this literature by identifying the specific mechanisms through which analysts influence corporate E&S performance and by providing an explanation for the observed gender differences in analyst impact. Leveraging novel computational linguistic methods and a substantially larger data set than prior studies (over 2.4 million analyst reports and 120,000 earnings call transcripts), we develop a novel active learning approach to accurately classify E&S-related discussions in equity research. Our findings reveal that gender differences in analyst impact stem from female analysts' greater propensity to use their "voice" on E&S issues, as well as their willingness to take "action" in response to negative E&S developments. By showing that female analysts' unique perspectives translate into concrete differences in their professional activities and ultimately to covered firms' E&S performance, we provide a clear delineation of the channels through which gender diversity among analysts can improve corporate E&S practices.

2. Hypothesis Development

Why do female analysts play a unique role in improving corporate E&S performance? First, there are some well-documented gender differences in values that might have implications for female analysts monitoring corporate E&S performance. Numerous studies across multiple disciplines have shown that relative to men, women have more prosocial and altruistic preferences, benevolence and universalism values, and express more concern and responsibility for the well-being of others (e.g., Beutel and Marini 1995; Schwartz and Rubel 2005; Bertrand 2011). Reflecting these gender differences, a number of studies show that women are more likely than men to support policies that regulate and protect citizens, consumers, and the environment, and social welfare, education, and health programs (Shapiro and Mahajan 1986; Gilligan, Ward, and Taylor 1988; Miller 2008; Alesina and Giuliano 2011). These non-pecuniary preferences of women align closely with investors' and corporate initiatives regarding E&S performance (Cronqvist and Yu 2017; Dyck, Lins, Roth, Towner, and Wagner 2023). The innate values and preferences of female analysts may drive them to prioritize and champion E&S issues in their professional roles.

Second, female analysts may improve E&S performance due to their superior abilities in analyzing and monitoring E&S issues, which can be attributed to self-selection and the broader effects of gender diversity. In a seminal paper, Kumar (2010) demonstrates that female analysts exhibit superior forecasting abilities compared to their male counterparts, as evidenced by bolder and more accurate forecasts. These superior abilities can be linked to better analysis and prediction of long-term E&S performance metrics, as female analysts' thoroughness and attention to detail may lead to more accurate assessments of a company's E&S initiatives. Moreover, while Lai et al. (2017) explore the effects of gender diversity in a different context (corporate boards and audit committees), their findings provide insights into the potential impact of female analysts on E&S performance. Gender-diverse boards are associated with increased monitoring, accountability, stricter ethical standards, and openness to diverse perspectives. Drawing parallels to the role of female analysts, these qualities may contribute to improved corporate E&S performance through more comprehensive evaluations of E&S risks and opportunities, and by encouraging companies to adopt more sustainable and socially responsible practices.

However, there are a number of reasons for female analysts not to care about or to effectively monitor E&S issues. Adams and Funk (2012) hypothesize that if females must emulate males to break the glass ceiling and advance to corporate director positions, gender differences in values and preferences might diminish or vanish. Consistent with this hypothesis, using a survey of directors in Sweden, Adams and Funk (2012) find that female and male directors differ systematically in their core values and risk attitudes, in ways that differ from gender differences in the general population. Moreover, consistent with gender differences in overconfidence (Croson and Gneezy 2009), Comprix, Lopatta, and Tideman (2022) show that female analysts are less aggressive in asserting their views during calls than their male counterparts. This behavioral trait could potentially offset any gender differences in monitoring E&S issues during calls, even had female analysts put greater emphasis on the well-being of others, community, and the environment than their male counterparts.

These competing perspectives and lack of evidence from prior literature underscore the need for a rigorous empirical investigation into the relationship between female analyst coverage and corporate E&S performance. Consequently, we formulate our null hypothesis as follows: There is no significant association between a firm's female equity analyst following and that firm's E&S performance.

3. Sample Formation and Overview

3.1. Sample formation

We measure corporate E&S performance in a number of ways: the overall E&S score (and its component scores) from Refinitiv's ESG database (formerly known as Thomson Reuters' ASSET4 database), carbon emissions from S&P Global Trucost, and workplace safety-related violations from Violation Tracker. We measure *Carbon emissions* as the natural logarithm of one plus the sum of annual Scope 1 and Scope 2 carbon emissions, following Sautner, van Lent, Vilkov, and Zhang (2023). The Violation Tracker data on workplace safety- or health-related violations include civil and criminal cases from more than 40 federal regulatory agencies; we remove violations in which the penalty or settlement is lower than $5,000. We measure a firm's social performance using both the dollar amount and frequency of workplace safety-related violation cases. *Workplace safety-related penalties* is the natural logarithm of one plus the total dollar amount of penalty incurred due to a firm's workplace safety- or health-related violations in a given year. *Workplace safety-related cases* is defined analogously.

Table 1 lists the steps taken to form our main sample, comprising 20,423 firm-year observations representing 3,567 unique firms.

3.2. Identifying female equity analysts

From the I/B/E/S Detail Recommendations file, we obtain a list of 903 unique brokerage houses and 12,640 unique analysts providing recommendations on U.S. equities over the period 2004−2020. I/B/E/S provides an abbreviated brokerage name in the variable ESTIMID, a unique brokerage identifier in the variable EMASKCD, the last name and first name initial of each analyst in the variable ANALYST, and a unique analyst identifier in the variable AMASKCD.

To unmask abbreviated brokerage names and analyst names from I/B/E/S, we manually search each brokerage's full name and its analysts from Capital IQ (supplemented by Bloomberg). Our matching process involves three steps: 1) we match abbreviated broker names in I/B/E/S (ESTIMID) to full broker names in Capital IQ based on resemblance; 2) we ascertain the match in Step 1 by matching analyst names in I/B/E/S (ANALYST) with those in Capital IQ using the last name and first name initial; and 3) we supplement the above two steps by checking whether Capital IQ analysts' stock coverage is the same as that by matched I/B/E/S analysts using Bloomberg's "*PEOP*" function. Of the 903 brokers in I/B/E/S, we are able to unmask full broker names for 785 (an 86.9% matching rate).

We then obtain individual analyst information including biography and prefix (Mr. versus Ms.) from their employment history in Capital IQ. We rely on the biography (i.e., "he" versus "she" is used when referring to an analyst) and the prefix(es) to determine an analyst's gender. In the end, we are able to unmask 10,657 out of the 12,640 unique analysts in the I/B/E/S Detail Recommendations file, achieving an 84.3% matching rate.[3]

Table IA1 in the Internet Appendix provides an overview of female analysts over time and across Fama-French 12 industries over the period 2004–2020. It is worth noting that the

[3] We rely on information from Capital IQ (supplemented by Bloomberg) to compute the number of female analysts and the number of analysts following a firm. We opt not to use the I/B/E/S Detail Recommendations file to construct the above two measures because had we done so, the assumption would have been that analysts without gender data from Capital IQ would have all been males.

patterns exhibited are largely consistent with those reported in Kumar (2010). The share of female analysts is relatively stable over our sample period, and female analysts are more heavily concentrated in the consumer non-durables, retail, and healthcare sectors.

3.3. Identifying female equity analysts in research reports

We download 2,434,739 analyst reports covering S&P 1500 constituent firms over the period 2004–2020 from Thomson One's Investext. We use the Stanza package to conduct named entity recognition (NER) in each report and extract identifying information including gvkey, lead analyst name, and broker name, resulting in 1,681,153 reports by 11,464 analysts from 822 brokers, covering 1,780 firms.[4]

To determine analyst gender in the analyst report sample, we match each analyst's name in Investext with our hand-collected gender data in the I/B/E/S-Capital IQ merged sample, as described in Section 3.2. Our matching process is as follows: 1) we match each broker in Investext to broker name and ID (EMASKCD) in the I/B/E/S-Capital IQ merged file; of the 822 unique brokers in Investext, we can link 292 brokers with EMASKCD – analysts affiliated with these 292 brokers produce 82% of the reports in our analyst report sample; and 2) for cases in which Investext has the lead analyst's full first name and full last name, we match each lead analyst name in Investext to full analyst name and ID (AMASKCD) in the I/B/E/S-Capital IQ merged file; we further verify this match by ensuring there is also a match with broker name-EMASKCD established in Step 1. In the end, we are able to uncover gender data for 6,644 analysts, representing 70% of the analysts affiliated with the 292 brokers in our analyst report sample.

[4] The sample of 1,780 firms is the overlapping sample between S&P 1500 constituent firms and our main sample of 3,567 unique firms listed in Table 1.

After removing analyst reports with missing analyst-level control variables, our final sample comprises 960,232 reports covering 19,274 firm-year observations for 1,686 unique firms.

3.4. Identifying female equity analysts in earnings conference calls

We download 129,302 earnings conference calls over the period 2007–2020 from Capital IQ. After matching with Compustat, we end up with 64,075 calls, covering 2,186 firms.[5]

We then match each analyst's name in calls with our hand-collected gender data in the I/B/E/S-Capital IQ merged sample, similar to steps taken in Section 3.3. We can link 384 brokers with EMASKCD – analysts from these brokers capture 83% of the analysts attending calls in our call sample. In the end, we are able to uncover gender information for 4,862 analysts, representing 62% of the analysts from the 384 brokers in our call sample.

After removing analyst-call observations with missing analyst-level control variables, our final sample comprises 259,801 analyst-call observations from 51,778 earnings calls covering 14,310 firm-year observations for 1,347 unique firms.

3.5. Sample overview

Table 2 provides the summary statistics for our sample. All continuous variables are winsorized at the 1st and 99th percentiles, and the dollar values are in 2021 dollars. The Appendix provides detailed variable definitions. We show that the sample mean/median E&S score is 0.420 (0.325), with the mean/median E(S) score at 0.412/0.281 (0.427/0.355); the sample mean (median) carbon emissions (in millions of metric tons) is 1.033 (0.036); the sample mean (median) dollar amount of workplace safety-related penalties is 9.741 (0)

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[5] The sample of 2,186 firms is a subset of our main sample of 3,567 firms listed in Table 1, suggesting that 61% of firms in our main sample hold earnings calls (as far as we can identify).

thousand; and the sample mean (median) number of such cases is 0.526 (0). Our key variable of interest is *N_female*, the number of female equity analysts covering a firm. The mean/median is 0.480 (0). About a third of firm-year observations in our sample have at least one female equity analyst following, with an average female analyst ratio of 7.3%. Conditional on having female analyst coverage, the average female ratio of analysts is 11%. The summary statistics for most other control variables are consistent with those in prior work (e.g., Chen, Dong, and Lin 2020; Starks, Venkat, and Zhu 2023).

Table IA2 in the Internet Appendix provides the Pearson correlation matrix. Examination of the correlation matrix suggests that multicollinearity is unlikely to be an issue.

4. Fine-tuning FinBERT for Classifying E&S-related Discussions via Active Learning

4.1. Why FinBERT?

To capture analyst monitoring through their research activities, we develop a machine learning approach to extract E&S-related information from 2,434,739 analyst reports and 129,302 earnings calls. Specifically, we employ active learning, a human-in-the-loop machine learning approach, to develop two domain-specific E&S text classification models to capture analysts' writing in research reports and questions raised during earnings calls about corporate E&S performance.

Our approach builds on FinBERT (Huang, Wang, and Yang 2023), a state-of-the-art large language model pre-trained by processing a large corpus of financial text, including annual/quarterly reports, analyst reports, and earnings calls, and learning to predict randomly masked words and determine if two sentences are adjacent in a document. After pre-training, the model generates a contextualized embedding vector for each sentence, which can be further fine-tuned and used as classification features for other tasks such as text classification. Because the model learns semantic (e.g., different meanings of words) and syntactic (e.g., phrases and sentence compositions) information from a large corpus during the pre-training step, Huang, Wang, and Yang (2023) show that the fine-tuning step requires only a relatively small training sample to achieve high text classification accuracy.

In this paper, we fine-tune FinBERT to classify whether texts in analyst reports or questions during calls are related to E&S issues. Our goal is to classify a passage of text into one of three categories: Environmental (E), Social (S), or neither (Non-E&S).[6]

Although Huang, Wang, and Yang (2023) trained a FinBERT-ESG model to classify sentences related to Environmental (E), Social (S), or Governance (G), we find that the performance of their model falls short when applied to our two corpora. This outcome is likely caused by the significant variation in language and style across different domains when discussing ESG topics. The FinBERT-ESG model was trained using firms' CSR reports and Management's Discussion and Analysis (MD&A) sections of 10-K filings. The language used in those disclosures differs from that employed by analysts writing from a capital market professional's perspective, or from the more colloquial expressions analysts use during Q&A sessions of calls. To account for these differences, we fine-tune the FinBERT model of Huang, Wang, and Yang (2023) using domain-specific training examples from analyst reports and calls, enhancing its ability to detect E&S-related discussions in these domains.

4.2. Constructing domain-specific training examples via active learning

We employ *active learning* – an algorithm that facilitates the efficient curation of domain-specific examples, thereby enabling the fine-tuning of two separate E&S text classification models, each designed specifically for analyst reports (calls).

[6] In the context of analyst reports, a passage refers to a sentence. Our goal is to classify each sentence into one of three categories: Environmental (E), Social (S), or neither (Non-E&S). In the context of calls, a passage refers to a question. Our goal is to classify each question into the same three categories; because E&S-related issues often span multiple sentences within a question, to avoid any information loss we refrain from breaking down a question into individual sentences.

Figure IA1 in the Internet Appendix presents a flowchart of the active learning process. As shown in the figure, in Step 1, we use keywords related to E&S issues to search for a set of initial training examples from the two corpora.[7] Passages containing those keywords are tentatively labeled as positive examples (E or S), and random passages are used as negative examples (Non-E&S). In Step 2, we use the initial training examples to fine-tune the FinBERT model into a *Noisy E&S model*. In Step 3, we use the *Noisy E&S model* to classify the initial training examples. Given the *Noisy E&S model*'s output, a subset of important examples is labeled by human annotators (Cormack and Grossman 2014).[8] In Step 4, those labeled examples are then used to further fine-tune the *Noisy E&S model* and produce the *Final E&S model*. We provide a self-contained technical appendix in the Internet Appendix that describes preprocessing and model training procedures step by step.

We observe that, following active learning, the performance of our model in E&S classification tasks shows significant improvement over the FinBERT-ESG model that Huang, Wang, and Yang (2023) fine-tuned using 2,000 labeled sentences from firms' CSR reports and MD&A sections of 10-K filings. Specifically, the three-class area under the curve (AUC) metric on the validation set improves from 0.85 (0.78) to 0.96 (0.97), and the classification accuracy improves from 0.67 (0.63) to 0.84 (0.88) for analyst reports (calls). Intuitively, the improvement we achieve over existing approaches can be attributed to our training data's close alignment with the language style analysts use in writing about E&S issues in reports (posing questions about E&S issues during calls).

4.3. Capturing E&S-related discussions

[7] Table IA3 in the Internet Appendix lists queries of corporate E&S issues.
[8] Table IA4 in the Internet Appendix lists some important examples identified by active learning protocols for human labeling.

After applying the fine-tuned FinBERT model to classify each sentence in an analyst report, we capture the frequency of discussions regarding E&S issues in a report using different indicator variables: *Having E&S sentences, Having E sentences,* and *Having S sentences*. These variables take the value of one if there is at least one relevant sentence in a report, and zero otherwise. We capture the intensity of analysts discussing E&S issues by using the natural logarithm of one plus the number of sentences related to E&S performance in a report (*Ln(1 + N_E&S sentences)*, *Ln(1 + N_E sentences)*, and *Ln(1 + N_S sentences)*). We obtain a similar set of measures for calls.[9]

Figures IA2 and IA3 in the Internet Appendix offer overviews of the temporal trends and industry distributions of E&S-related discussions in reports and E&S-related questions during calls. Figure IA2 reveals an overall upward trend in E&S discussions over the years. Notably, discussions pertaining to environmental issues in reports exhibit a significant uptick after 2008, probably driven by regulations outlined in the Presidential Climate Action Plan since 2008 and significant investments in clean energy outlined in the American Recovery and Reinvestment Act of 2009. We observe that while analysts tend to write more about environment-related issues in their reports, they tend to raise more social-related questions during calls.[10] In terms of industry breakdown in Figure IA3, it is not surprising that discussions of environmental issues are heavily concentrated in resource-intensive industries that tend to have larger environmental footprints, such as utilities, chemicals, energy,

[9] Table IA5 in the Internet Appendix provides examples of E&S-related sentences identified in reports. Table IA6 in the Internet Appendix provides examples of E&S-related questions identified in calls.
[10] There are two possible reasons for analysts to write more about environmental issues in their reports. First, environmental performance is considered highly value-relevant by investors, see, for example, Griffin, Lont, and Sun (2017) and Bolton and Kacperczyk (2021). In contrast, social performance is more controversial and harder to quantify, and, as a result, is more likely to be raised during calls. Second, earnings calls and analyst reports play distinctly different roles in shaping a firm's information environment, whereby the former provides a platform for analysts to question unclear firm policies and practices, while the latter incorporates all value-relevant information into a report. Hence, analysts tend to provide relatively more discussion on environmental issues in their reports and ask more clarifying questions about social issues during calls. Consistent with the above argument, Figure IA4 in the Internet Appendix shows different E&S issues discussed in reports versus those raised during calls.

manufacturing, and consumer durables. In contrast, discussions of social issues occur with a more even distribution across industries.

5. Main Results

5.1. Female equity analysts and corporate E&S performance

To test our null hypothesis, we employ the following panel data regression:

$$E\&S\ performance_{i,t+1} = \alpha + \beta_1\ N\_female_{i,t} + \beta_2 Firm\ characteristics_{i,t} + Industry \times Year\ FEs + \varepsilon_{i,t}, \tag{1}$$

where the dependent variables are different measures of corporate E&S performance: *E&S score* (and its component scores), *Carbon emissions*, *Workplace safety-related penalties*, and *Workplace safety-related cases*. The key variable of interest is the number of female analysts following a firm (*N_female).* The control variables largely follow Ferrell, Liang, and Renneboog (2016), Dyck et al. (2019), Chen, Dong, and Lin (2020), Starks, Venkat, and Zhu (2023), and Griffin, Guedhami, Li, and Lu (2021). We include industry × year fixed effects to control for industry-specific time trends. Because our panel data set includes small firms with short time series, including industry × year fixed effects is our preferred specification (Gormley and Matsa 2014).

5.1.1. Using Refinitiv E&S scores

Table 3 Panel A presents the regression results when the dependent variables are *E&S score* and its component scores. We show that there is a positive and significant association between the number of female analysts following and *E&S score*. In contrast, there is a negative and significant association between the number of analysts following (*Analyst coverage*) and *E&S score*. The negative association is consistent with the fact that analysts tend to focus on earnings performance, and that underinvestment in E&S performance can result in a boost in short-run performance, as investment in E&S performance is often taken as an item in SG&A expenses (Di Giuli and Kostovetsky 2014; Chen, Dong, and Lin 2020). Moreover, given that only about 7% of financial analysts are female in our sample, the negative coefficient on *Analyst coverage* is largely driven by male analysts. These results provide new evidence suggesting that even among finance professionals, there remain gender differences in values relating to corporate E&S performance.[11]

In terms of economic significance, adding one more female analyst (*N_female*) is associated with a 0.014 increase in *E&S score* (ranging from 0 to 1), which is equivalent to a 3.3% (0.014/0.420) increase relative to the mean E&S score, and a 4.9% (0.014/0.287) standard-deviation increase in *E&S score*.[12]

In an alternative specification, we include firm and year fixed effects to control for time-invariant firm unobservables and time trends that might drive both female analyst coverage and corporate E&S performance. Table IA8 Panel A in the Internet Appendix presents the regression results. We show that there remains a positive and significant association between *N_female* and *E&S score*.

As discussed earlier, we primarily rely on information from Capital IQ to determine analyst gender and to compute analyst coverage and female analyst coverage. To mitigate the problem of missing (unidentified) analysts, as a robustness check, we use *Female analyst ratio* or *Having female analyst* instead of the number of female analysts (*N_female*), assuming that this ratio in our identified analyst sample is a good proxy for the same ratio in

[11] Table IA7 in the Internet Appendix presents the results from our main specification in Equation (1) using alternative data sets to measure E&S performance: Thomson Reuters' ASSET4, MSCI's KLD Stats, and Morningstar's Sustainalytics. We show that our main findings remain.

[12] This economic significance is comparable to other important factors identified in prior literature. For example, Dyck, Lins, Roth, and Wagner (2019) find that a one-standard-deviation increase in a firm's institutional ownership is associated with a 4.5% increase in its environmental performance. Hsu, Li, and Pan (2023) show that a one-standard-deviation increase in the share of female directors on corporate boards is associated with a 12% increase in its environmental performance. This economic significance is also comparable to other control variables in our baseline regression. We find that the economic significance of *N_female* (i.e., the change in E&S score driven by adding one more female analyst) is higher than that driven by a one-standard-deviation increase in *Analyst coverage*, *ROA*, *CEO duality*, and *Institutional ownership*. The economic significance of *N_female* is lower than that of *Firm size*, *Tobin's Q*, *Leverage*, *SG&A*, and *Cash holdings*.

the full analyst sample if the missing data problem in Capital IQ applies equally to both male and female equity analysts in the population. Table IA8 Panels B and C present the results. Our main findings remain.

To explore any potential non-linear effect of the number of female analysts on corporate E&S performance, we introduce four indicator variables for a firm having one, two, three, or four female analysts (the maximum number of female analysts covering a firm in our sample). Table IA8 Panel D presents the results. We show that the positive association between female analyst coverage and E&S performance is significant only when there is more than one female analyst following.[13]

Table IA9 in the Internet Appendix examines the dynamic effects of changes in a firm's female analysts following changes in its E&S performance. We show that any change in a firm's female analyst coverage does not lead to immediate changes in a firm's E&S performance, but rather starts to show an effect from the second (for gaining female analyst coverage) or third year (for losing female analyst coverage). The results suggest that the effect of female analyst coverage on corporate E&S performance is gradual and persistent, and is unlikely driven by reverse causality.

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[13] One possible interpretation of our main findings is that they are not due to gender differences in values, but due to the organizational culture of a brokerage with which a female analysis is affiliated. For example, a large brokerage might be under more scrutiny to promote diversity, inclusion, and CSR than a small one. Consistent with this conjecture, in our sample, the share of female analysts at the top 10 brokers is 15.7%, and the share of female analysts at the non-top 10 brokers is 11.0%. To examine this possible interpretation, we repeat our analysis by replacing our female analyst coverage variable with two measures: coverage by female analysts from the top 10 brokers (by size) and that from the non-top 10 brokers. Table IA8 Panel E in the Internet Appendix presents the results. We show that both female coverage variables are positively and significantly associated with corporate E&S performance. In addition, we employ a F-test of differences between the two coefficients and the p-value (> 0.1) of the F-test indicates that the coefficient on *N_female_Top10* is not significantly different from that on the *N_female_non-Top10*. This analysis suggests that our main findings are unlikely driven by different broker cultures. Another possible interpretation of our main findings is that they are driven by gender differences in experience. For example, female analysts are often younger than their male counterparts and hence are more attuned to E&S issues. In Table IA8 Panel F, we show that our main findings remain controlling for gender differences in general and/or firm-specific experience among following analysts. Table IA8 Panel G show that our main findings remain controlling for a firm's socially responsible investment (SRI) fund ownership (Heath, Macciocchi, Michaely, and Ringgenberg 2023). This finding helps address the concern that our main finding is due to monitoring of E&S-conscious investors. In untabulated analysis, we split the sample into two subsamples with the highest/lowest number of analysts in the top/bottom five Fama-French industries. We show that our main findings remain in those two subsamples.

5.1.2. Using real E&S outcomes

Table 3 Panel B presents the regression results when the dependent variables are measures of real E&S outcomes. We show that there is a negative and significant association between the number of female analysts following a firm, and its carbon emissions, dollar amount of penalties incurred due to workplace safety/health violations, and frequency of workplace violation cases. The evidence consistently suggests that a firm's female analyst coverage is significantly associated with some real E&S outcomes, such as reduced carbon emissions and enhanced workplace safety.

5.2. Identification strategy: A DID approach

5.2.1. A quasi-natural experiment: Broker closures

To assess whether the identified association between a firm's female equity analysts following and that firm's E&S performance is likely to be causal, we exploit a quasi-natural experiment, broker closures, where terminations of female analyst coverage are the result of brokerage firms closing their research departments. Identification requires that such terminations correlate with a drop in female analysts, but do not otherwise correlate with corporate E&S performance. According to Kelly and Ljungqvist (2012), the closures of brokers are primarily driven by economic challenges in the equity research industry, rather than the E&S performance of the firms they cover.[14] As far as we are aware, we are the first in the literature to use broker closures to create an exogenous drop in the number of *female* analysts covering a firm.

[14] For example, the closure of JB Hanauer Co. in 2007, following its acquisition by RBC Dain Rauscher, was primarily due to strategic consolidation within the industry. This acquisition was part of RBC's broader strategy to expand its presence in key U.S. markets and enhance its wealth management services. See Investment Executive.

To identify broker closures over the period 2005−2019, we proceed as follows.[15] First, using the I/B/E/S Detail Recommendations file, we obtain a list of brokers that stopped providing stock recommendations and were covered by Capital IQ (to obtain information on analyst gender). Second, we exclude broker closures due to mergers.[16] Third, for the remaining cases, we search Capital IQ to verify the status of each disappeared broker and/or if its research division is out of business. Since Capital IQ does not provide the exact date of a broker's closure, we further search for a broker's closure date in Factiva and the Financial Industry Regulatory Authority's (FINRA) BrokerCheck database. Finally, we exclude closures that only affected male analysts and end up with 79 broker closure events.[17]

5.2.2. Identifying the treated and control firms

To form the treated firm sample, following Kelly and Ljungqvist (2012) and Cen, Chen, Dasgupta, and Ragunathan (2021), we first identify analysts who worked for those brokers that disappeared from the I/B/E/S Unadjusted Detail History file (by not issuing earnings forecasts) during the year after the broker's closure date.[18] On average, a closure

[15] Although our sample period is 2005–2021, we collect data on closure events until 2019 so that we have at least one year of the post-closure period to conduct the DID analysis.
[16] To identify broker closures due to mergers, we start with a sample of completed deals involving financial institution targets from the SDC Mergers and Acquisitions (M&A) database over the period 2005−2018. Specifically, we define a deal involving financial institutions if its target macro industry description (TTF_MACRO_DESC) is "Financials." We include only completed deals whose completion date (DATEEFF) is after January 1, 2005. We match I/B/E/S broker names with target firm names in SDC. Given that matching at the target firm level fails to capture deals that take place at its parent level, we manually check the remaining unmatched brokers using the FactSet database. FactSet tracks the ownership structure of financial institutions globally and records the history of M&A transactions at either the parent's or the subsidiary's level. For deals identified in FactSet, we further search merger-related information in Google, Factiva, and Capital IQ to ensure accuracy.
[17] As a result, the sample period for the DID analysis ends in 2017 as broker closures after 2017 only affected male analysts.
[18] In theory, the event date should be a broker's exit date. In practice, broker closure dates (month) from Factiva and the FINRA BrokerCheck database do not always correspond with broker exit dates (month) from the I/B/E/S file as the completion of a broker's closure might take several months. Since there is no easy way of reconciling these event dates when they differ, we follow prior studies (see, for example, Kelly and Ljungqvist 2012; Derrien and Kecskés 2013) and use a six-month "event period" (denoted *t*) centered around a broker's closure date.

event affects 55 analysts, comprising 7 female analysts and 48 male analysts.[19] We then merge firms covered by those exited brokers with the baseline sample of 20,423 firm-year observations in Table 3 Panel A and retain only firms that have non-missing E&S scores and control variables in both years *t-1* and *t+1* – our estimation window includes one year before (*t-1*) and one year after (*t+1*) the event period following Chen, Harford, and Lin (2015).[20] Finally, we keep only firms that are previously covered by a female analyst from an exited broker and hence will lose such coverage due to broker closure.[21] The treated firm sample comprises 177 firms (representing 145 unique firms) associated with 24 broker closure events. Figure IA5 presents the temporal distribution of the 24 closures over the period 2005–2017 that result in a drop in female analyst coverage. The figure shows that the closure events are spread out fairly equally over time.

Table IA10 lists the 24 broker closure events, the number of the treated firms previously covered by a female analyst from an exited broker, and the number of industries covered by the broker at the time of closure. We note that, on average, sample treated firms are covered by four analysts; sample broker closures involve two female analysts; each sample female analyst covers three firms; and these sample broker closures do not cluster in specific industries.

To identify the control firms, we first remove the treated firms from the baseline sample in Table 3 Panel A and retain only firms that have non-missing E&S scores and

[19] For 22 out of the 24 broker closure events in our sample, no analyst found a sell-side job and continued covering the same firms in the year after their broker's closure. For the remaining two events, we do not find any gender differences among analysts who maintained their coverage after starting a position at a different broker. For example, at Wells Fargo Securities, 65% of the female analysts and 52% of the male analysts found sell-side analyst jobs, and continued to cover the same firms after their broker's closure. These findings alleviate the concern that brokers in our identification test exhibited different hiring practices for female versus male analysts.

[20] Since our event period *t* spans six months, year *t-1* is defined as the last fiscal year before the event, and year *t+1* is defined as the first complete fiscal year after the event. For example, if a firm has a December fiscal year-end and the event date is March 31, 2001, year *t-1* (*t+1*) would be December 31, 2000 (2002), respectively.

[21] It is worth noting that since brokers rarely assign more than one analyst to cover a firm, a broker closure event is unlikely to result in a drop in both female and male analyst coverage of the same firm. We find no such cases in the treated firm sample.

control variables in consecutive years. Since the treated and control firms could differ across various dimensions, we employ Coarsened Exact Matching (CEM, Iacus, King, and Porro 2011) to form the matched treated and control firms. Specifically, we match each treated firm with control firms based on year *t-1* values of E&S scores and control variables in Table 3 Panel A.[22] Our final matched sample consists of 105 treated firms and 1,197 control firms, for a total of 2,604 (= 2 × (105 + 1,197)) firm-year observations.[23]

5.2.3. The DID regressions

To investigate the effect of an exogenous drop in female analyst coverage on corporate E&S performance, we employ a DID specification as follows:

$$E\&S\ performance_{i,t+1} = \alpha + \beta_1\ Treated_i \times Post_{i,t} + \beta_2\ Post_{i,t} + \beta_3 Firm\ characteristics_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{i,t}, \quad (2)$$

where $Treated_i$ is an indicator variable that takes the value of one if firm *i* has experienced an exogenous drop in female analyst coverage due to broker closures, and zero otherwise. $Post_{i,t}$ is an indicator variable that takes the value of one in the year after broker closures (*t+1*), and zero in the year before (*t-1*). The standalone indicator, $Treated_i$, is absorbed by our inclusion of firm fixed effects as a treated firm is not used as control firm in our setting. Firm and year fixed effects are included to control for time-invariant firm characteristics and temporal trends, respectively.

[22] The CEM method starts by temporarily categorizing, or "coarsening," each matching variable into meaningful groups. It then performs exact matching on those coarsened variables, ensuring that the treated and control firms share the same value for each of the coarsened variables. The method is shown to effectively reduce imbalance between the treated and control groups, resulting in a more accurate estimation of any causal effect (Iacus, King, and Porro 2011).

[23] Baker, Larcker, and Wang (2022) show that staggered DID estimates are biased if the research setting contains relatively few never-treated units (where earlier-treated units are used as the control group for the later-treated units, producing biased estimates). It is worth noting that in our setting, to identify matched control firms, we first remove treatment firms from the sample. As a result, our DID estimates are not subject to their critique.

Table 4 Panel A presents the results examining the effect of broker closures on female analyst coverage. We show that the coefficient on the interaction term *Treated* × *Post* is negative and significant, suggesting that broker closures lead to a significant drop in female analyst coverage of their previously covered firms.[24] In Panel B, columns (1)-(3) present the results examining the effect of an exogenous drop in female analyst coverage on corporate E&S performance. We show that the coefficient on the interaction term *Treated* × *Post* is negative and significant, suggesting that an exogenous drop in female equity analyst coverage leads to a significant decrease in corporate E&S performance. In terms of economic significance, using column (1) as an example, the E&S performance of the treated firms (with a drop in female analyst coverage due to broker closures) decreases by 7.3% (0.024/0.331) relative to the mean, compared to that of the matched control firms (without experiencing a drop in female and/or male analyst coverage). Panel C presents the DID regression results using measures of real E&S outcomes: *Carbon emissions*, *Workplace safety-related penalties*, and *Workplace safety-related cases*. We show that the coefficient on the interaction term *Treated* × *Post* is positive and significant, suggesting that an exogenous drop in female equity analyst coverage leads to significantly worse real E&S outcomes including increased carbon emissions and more workplace safety violations. In terms of economic significance, losing one female equity analyst leads to approximately 8,800 additional metric tons of CO2 emissions, $15,000 in additional workplace-related penalties, and one additional workplace-related case. Overall, the DID analysis suggests that there is a causal effect of female analyst coverage on firm-level E&S performance.

Although we are the first in the literature to employ broker closures to establish the causal effect of female analyst monitoring on corporate E&S performance, we are mindful of

[24] In untabulated analysis, we do not find that broker closures lead to a significant drop in female analyst coverage of their previously covered firms in year *t+2*, suggesting that the effect of closures on analyst coverage takes place within the first year after such closures.

the critique associated with "reusing natural experiments" raised by Heath, Ringgenberg, Samadi, and Werner (2023). They show that reusing natural experiments whereby after a natural experiment is first used, other researchers often reuse the setting, examining different outcome variables, creates the multiple hypothesis testing problem that calls for a re-evaluation of conventional p-values and various remedies. It is important to note that our setting is new in the literature, as we focus on a specific subset of broker closures that result in a drop only in the number of female analysts following a firm. Our specific setting helps mitigate some of the concerns raised by Heath et al. (2023). Nevertheless, to further establish the intended causal effect, we conduct a number of robustness tests and additional analyses.

We first show that the exogenous drop in female analyst coverage does not lead to any significant deterioration in firms' corporate governance performance (*G score*, Table 4 Panel B column (4)): The coefficient on the interaction term *Treated* × *Post* is insignificant. Comparing columns (1)-(3) with column (4) suggests that female analyst monitoring of corporate E&S performance is not through the usual governance channel as measured by *G score*. In other words, female analyst monitoring of corporate E&S performance is distinct from analysts' governance role in general (e.g., Yu 2008; Chen, Harford, and Lin 2015).

We next conduct a placebo test wherein we measure the treatment effect on the dependent variable of interest generated by a false treatment. We repeat the DID analysis using a sample of pseudo treated firms, i.e., firms that lost coverage from male analysts due to broker closures, resulting in 1,632 treated firm-year observations, and the same control firms as in Panel B. Table 4 Panel D presents the results. We show that the coefficient on the interaction term *Treated* × *Post* is not significantly different from zero, suggesting that there is no significant change in corporate E&S performance after firms only lose male analyst coverage.

Finally, we examine the relation between female analyst E&S-related discussions, female analyst coverage drop, and subsequent negative E&S incidents using the same treatment sample. On average, the sample treated firms are followed by four analysts, suggesting that losing one will be visible to a covered firm. The number of E&S-related negative news items from RepRisk is our measure for negative E&S incidents: *Ln(1 + N_E&S incidents)*. Table 4 Panel E presents the results. We show that the coefficient on the interaction term *Post* × *Having E&S discussions* is positive and significant, suggesting that an exogenous drop in female analysts who had E&S discussions in their reports prior to departure leads to significantly more E&S incidents compared to those (dropped) female analysts who did not discuss E&S issues in their reports. Results from column (3) further show that it is female analysts' scrutiny of social issues that really matters; losing a female analyst covering social issues in her reports due to broker closures results in significantly more negative social incidents, compared to losing a female analyst not covering social issues.

Our findings above add to one strand of the analyst literature showing that corporate managers pay attention to their analyst coverage and learn from analysts' insights (e.g., Anantharaman and Zhang 2011; Mola, Rau, and Khorana 2013; Guo and Zhong 2023). Importantly, we show that corporate managers are also opportunistic cutting E&S investments when monitoring female analysts are gone.

We conclude that the effect of female analyst coverage on corporate E&S performance is likely causal.

6. Exploring Analysts' Means of Influence

Analysts have several potential means of influencing the firms they cover. One such means is through the production of research reports, which typically include earnings forecasts, stock recommendations, and target prices. These reports provide analysts with an opportunity to express concerns about the firms they cover. Another potential avenue of influence is through frequent interactions with management during earnings conference calls, in which analysts can question various aspects of a firm's business operations.

Based on these potential channels of influence, we propose two possible monitoring mechanisms through which female equity analysts could help shape corporate E&S performance. The first mechanism is via their "voice," whereby female analysts not only engage in more discussions or pose more questions about a firm's E&S issues compared to their male counterparts, but also adopt different perspectives. The second mechanism is via their "action," whereby female analysts are more likely to downgrade stocks and/or lower target prices following negative E&S discussions in their reports. These actions could exert pressure on firms to improve their E&S performance in order to maintain favorable analyst coverage and recommendations.

To capture analysts' voice, we apply the fine-tuned FinBERT models described in Section 4 to capture analysts' discussions of E&S issues in reports and the associated regression analysis, and their questions of E&S issues during calls and the associated regression analysis. To capture analysts' action, we examine whether there are gender differences in analysts' stock recommendations and target price forecasts following their negative discussions of E&S issues in reports. Finally, we also explore whether investors are paying attention to female analysts' E&S-related discussions in their reports.

6.1. E&S issues in analyst reports

Table 5 Panel A presents the summary statistics at the report level. We show that 29.6% of the reports in our sample touch upon firms' E&S issues, and that the average number of E&S-related sentences in a report is 0.9 (among reports discussing E&S issues, the average number of E&S-related sentences in a report increases to 2.6 (untabulated)). Analysts are more likely to write about environmental issues than social issues. The probability for the former is 22.2%, whereas the probability for the latter is 13.4%.

Panel B presents the regression analysis at the report level. Our analyst-level control variables largely follow prior literature, such as Clement (1999) and Hong and Kacperczyk (2010). We include firm × year fixed effects to control for time-varying unobservable firm characteristics that may drive both female analyst coverage and their monitoring of E&S issues. We also include brokerage × year fixed effects to control for time-varying unobservable brokerage characteristics that may affect the decisions female analysts make on which firms to include in their research portfolios and these analysts' monitoring of corporate E&S performance.

We show that there is a positive and significant association between an analyst being a female and her reports discussing E&S issues. In terms of economic significance, using the probability of a female analyst discussing E&S issues as the dependent variable (column (1)), we show that the presence of a female analyst is associated with a 1.6 percentage point-increase in the probability of that analyst writing about E&S issues in her reports. This effect is economically large given that the sample average probability is 29.6%, representing a 5.4% (1.6%/29.6%) increase.

6.2. E&S questions during earnings conference calls

Table 6 Panel A presents the summary statistics at the analyst-call level. We show that 15.3% of the analysts ask about firms' E&S issues during calls, and that the average number of E&S-related questions in a call is 0.2 (among calls with E&S-related questions, the average number of E&S-related questions in a call is 1.2 (untabulated)). Analysts are more likely to ask questions about social issues than environmental issues. The probability of the former is 12.0%, whereas the probability of the latter is 3.9%.

Panel B presents the regression analysis at the analyst-call level. The analyst-level control variables and different fixed effects are similar to the analyst report analysis in Section 6.1. We show that there is a positive and significant association between an analyst being a female and her questions relating to E&S issues. In terms of economic significance, using the probability of analysts asking E&S-related questions during a firm's call as the dependent variable (column (1)), we show that the presence of a female analyst is associated with a 1.0 percentage point-increase in the probability of analysts asking about E&S issues. This effect is economically large given that the sample average probability is 15.3%, representing a 7% (1.0%/15.3%) increase.

We next examine the relation between analysts' E&S-related discussions in reports and/or analysts' E&S-related questions during calls and firms' E&S performance. The analysis is at the firm-year level. *Ln(1 + N_E&S sentences)* is the natural logarithm of one plus the average number of E&S-related sentences in reports written by analysts covering a firm in a given year. *Ln(1 + N_E sentences)*, *Ln(1 + N_S sentences)*, *Ln(1 + N_E&S questions)*, *Ln(1 + N_E questions)*, and *Ln(1 + N_S questions)* are defined analogously. Table IA11 presents the results.

We first show that there is a positive and significant association between E&S discussions either in reports or during calls and corporate E&S performance, suggesting that analysts play a monitoring role in corporate E&S performance through their research activities. Importantly, we show that the coefficients on the interaction terms between *N_female* and any above measure of E&S discussions (questions) are positive and significant, suggesting that analysts' E&S discussions are more influential in firms with more female analysts following. Bradley, Mao, and Zhang (2022) find that managers are more likely to discuss safety issues on calls in the presence of more analysts who cover the firm, suggesting a potential mechanism for the effect of analyst coverage on injury rates. We extend their findings by highlighting that it is female analysts who monitor corporate E&S performance, not analyst coverage in general.

To further investigate the thematic differences in how female and male analysts discuss E&S issues, we employ a Structural Topic Modeling (STM) approach (Roberts et al. 2014). STM allows us to discover latent topics within the corpus of analyst reports and earnings call questions while explicitly modelling the relationship between analyst gender and topic prevalence. It enables us to study how gender influences the extent in which analysts discuss certain E&S themes. The details of our STM analysis are provided in the Internet Appendix. Table IA12 presents the top words for each topic in each corpus, along with our assigned labels. Figure IA6 shows consistent and significant differences in the topics emphasized by female and male analysts across all four corpora. Female analysts tend to focus more on topics related to regulatory compliance, risk management, strategic planning, and stakeholder impact. In contrast, male analysts place greater emphasis on financial metrics, operational efficiency, and industry-specific dynamics. Furthermore, female analysts' E&S discussions are likely to be more impactful due to their focus on strategically important topics such as customer impact, market opportunities, and brand loyalty. Together, these findings suggest that female analysts adopt a more holistic, stakeholder-oriented perspective when assessing firms' E&S performance, while male analysts take a more shareholder-oriented view.

6.3. Gender-specific consequences of negative E&S discussions

We use the pre-trained FinBERT-tone model from Huang, Wang, and Yang (2023) to classify sentiment (positive, negative, and neutral) in E&S-related sentences in reports. At the sentence level, we capture tone by employing an indicator variable, *Tone*, that takes the value of 1 if the probability of positive sentiment is greater than 50%, -1 if the probability of negative sentiment is greater than 50%, and zero otherwise. At the report level, *Negative E&S*

tone is the negative value of the average tone of E&S-related sentences. *Negative non-E&S tone* is defined analogously. We examine whether there is any gender difference in analysts' research output (i.e., stock recommendations, target prices, and earnings forecasts) following their negative discussions of E&S issues. Table 7 presents the results at the report level.

We show that the coefficient on the interaction term *Female* × *Negative E&S tone* is positive and significant when the dependent variable is stock recommendation (target price), suggesting that female analysts are more likely to downgrade stocks (lower target prices) compared to male analysts when having negative E&S discussions in reports. In terms of economic significance, a change in *Negative E&S tone* from neutral to negative (or from positive to neutral) results in female analysts being 15.6% more likely to downgrade the stock and 4.5% more likely to lower the target price than their male counterparts. We further show that the coefficient on the interaction term *Female* × *Negative E&S tone* is not significantly different from zero when the dependent variable is earnings forecast.[25] Derrien, Krüeger, Landier, and Yao (2023) present international evidence that after learning about negative ESG incidents, analysts significantly lower their earnings forecasts at short and longer horizons. Complementary to their findings, we show that there are also gender differences in analyst monitoring firms' E&S practices through stock recommendation and target price revisions.

6.4. The information content of analysts' E&S discussions

To investigate the information content of analysts' E&S discussions in reports, we conduct an event study relating three-day cumulative abnormal returns (CAR) around the report date, *CAR[-1,+1],* to measures of analysts' E&S discussions controlling quantitative

[25] The 15.6 percentage point-increase is calculated from 0.049 × 100/0.314 where the denominator 0.314 is sample average *Recommendation down*, and the 4.5 percentage point-increase is calculated from 0.015 × 100/0.334 where the denominator 0.334 is the sample average *Target price down*.

and qualitative summary measures of a report, and analyst and firm characteristics (Huang, Zang, and Zheng 2014; Huang et al. 2018).[26] Table 8 presents the regression results.

We show that the coefficient on the interaction term *Female* × *Negative E&S tone* is negative and significant, suggesting that female analysts' E&S discussions in a report provide information beyond that provided by its quantitative and qualitative measures. In terms of economic significance, a change in *Negative E&S tone* from neutral to negative (or from positive to neutral) by female analysts is associated with a three-day abnormal negative return of 54.1 basis points, corresponding to a $120.1 million decrease in market value for an average firm in the sample, compared to their male counterparts.[27] It is worth noting that the effect documented above is the direct information effect of female analysts' E&S discussions in reports, and that there are also indirect effects via stock recommendation and target price revisions shown in Table 7.

In summary, our analyses in this section establish a clear link between female analysts' research activities and their monitoring role in corporate E&S performance. We find that female analysts not only focus more on E&S issues in their writings and questions, but also exhibit systematically different thematic emphases compared to their male counterparts. These differences in perspective and focus lead to tangible outcomes, with investors reacting more significantly to female analysts' negative tone in E&S discussions and female analysts being more likely to take action by downgrading stocks and lowering target prices following negative E&S discussions. Ultimately, these findings suggest that female analysts' distinct voice and action translates into improved E&S ratings for the firms they cover.

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[26] For this analysis, we remove 841,959 reports due to companies with multiple reports, 10,759 reports due to companies issuing earnings announcements, and 4,709 reports due to companies issuing earnings guidance, in the CAR window.

[27] The 54.1 basis point-decrease is calculated from $1 \times 0.541 \times 100$, and the $120.1 million-decrease in market capitalization is calculated from 0.541% × $22.2 billion where $22.2 billion is the sample average market capitalization.

7. Additional Investigations

7.1. Female analyst experience

Prior studies show that analysts with more experience incorporate earnings news more completely and promptly in their forecasts; these analysts also generate greater stock market reactions when making their forecasts compared to analysts with less experience (Bradley, Gokkaya, and Liu 2017). In our context, we expect that the voice of female analysts regarding corporate E&S performance is more likely to be heard when these analysts are more experienced and highly regarded by institutional investors, resulting in improved corporate E&S performance. We employ three different measures of analyst experience and reputation following prior work (Yu 2008; Bradley, Gokkaya, and Liu 2017): general experience, firm experience, and All-Star status (as designated by Institutional Investor magazine). Table IA13 in the Internet Appendix presents the results.

In Panels A and B, we show that the coefficients on the interaction terms *N_female* × *Female more general experience* and *N_female* × *Female more firm experience* are positive and significant, suggesting that female analysts, especially those with more general and/or firm-specific experience relative to other analysts covering the same firm, are more influential in their monitoring roles, which results in greater improvements in firm-level E&S performance. In Panel C, we examine whether and how All-Star female analysts are associated with firm-level E&S performance. We first show that both the number of female equity analysts and the indicator variable *Female star analyst* are positively and significantly associated with corporate E&S performance. We further show that the coefficient on the interaction term *N_female* × *Female star analyst* is not significantly different from zero, suggesting that having one additional female analyst is of little import once the presence of at least one female star analyst is taken into account.

7.2. Female directors and female executives

Given the discussion on gender differences in values in Section 2, we expect that the presence of female directors and officers could play a similar role in enhancing corporate E&S performance. Table IA14 in the Internet Appendix presents the results.

Panel A presents the regression results involving female directors and female equity analysts. We first show that both the number of female equity analysts and the number of female directors are positively and significantly associated with corporate E&S performance, with one exception: when the dependent variable is *E score*. We further show that the coefficient on the interaction term *N_female* × *N_female directors* is not significantly different from zero, suggesting that the role of female analysts in enhancing corporate E&S performance is invariant to the presence of female directors. Panel B presents the regression results involving female executives and female equity analysts.[28] We first show that both female executives and female equity analysts are positively associated with corporate E&S performance. Again, we show that the coefficient on the interaction term *N_female* × *N_female executives* is not significantly different from zero, suggesting that the role of female analysts in enhancing corporate E&S performance is invariant to the presence of female executives.[29]

In summary, the results in Table IA14 help support our conjecture that female analysts play a unique monitoring role in firms' E&S practices.

7.3. Female equity analysts' E&S discussions and career outcomes

[28] For this analysis, our sample size is reduced because data on the gender of executives is from ExecuComp, which covers only S&P 1500 constituents.

[29] In untabulated analysis, when including *N_female, N_female directors,* and *N_female executives* in one regression specification, we find that both female analysts and female directors have positive and significant effects on corporate E&S performance, while female executives lose significance. In terms of economic significance, adding one more female director is associated with an 8.5% increase in *E&S score* and adding one more female analyst is associated with a 2.1% increase in *E&S score*.

Career concerns play a central role in analysts' allocation of effort (Harford, Jiang, Wang, and Xie 2019). The positive association between a firm's female analyst coverage and its E&S performance may reflect these analysts' career concerns instead of gender differences in values. To explore this alternative interpretation, we employ two career outcome measures, *Star analyst* and *Forecast accuracy* (Groysberg, Healy, and Maber 2011), and examine whether there is any association between female analyst monitoring corporate E&S performance and their likelihood of achieving All-Star status and forecast accuracy. Table IA15 presents the results.

We find that none of the coefficients on the interaction terms *Female* × *Ln(1 + N_E&S sentences)* and *Female* × *Ln(1 + N_E&S questions)* is statistically different from zero, suggesting that gender differences in values with implications for female analysts monitoring corporate E&S performance are distinct from analyst career incentives in general. The results help support our conjecture that gender differences in values are the main driver of female analysts' monitoring corporate E&S performance.

7.4. Sub-period analysis: The Paris Agreement

To examine whether there is any temporal variation in the strength of the positive association between a firm's female analysts following and its E&S performance due to shifting societal trends, we use 2016, the year after the passage of the Paris Agreement, as the cutoff and divide our sample period 2005–2021 into two sub-periods 2005–2015 and 2016–2021. Table IA16 presents the results.

We find a positive and significant association between female analysts following and corporate E&S performance in both sub-periods, suggesting that the effect of female analyst monitoring on corporate E&S performance is not solely driven by public attention to climate risk. These findings support our conjecture, indicating that gender differences in values, rather than the growing awareness of E&S issues over time, underpin our main findings.

8. Conclusions

Using a hand-collected sample of over 10,000 sell-side equity analysts with gender data and both E&S ratings and measures of real E&S outcomes over the period 2005–2021, we show that there is a positive and significant association between the number of female analysts covering a firm and that firm's E&S performance. Using broker closures as an exogenous shock to the number of female analysts following, our difference-in-differences analysis suggests that female analyst coverage has a causal effect on firms' E&S performance.

To delineate the means of influence through which female analysts help improve corporate E&S performance, we adopt an active learning approach to fine-tune FinBERT in order to uncover E&S-related discussions in analysts' research activities. We show that female equity analysts are more likely to discuss firms' E&S issues in their reports, and are also more likely to raise questions about those issues during calls than their male counterparts. We further show that, following negative E&S-related discussions in reports, female equity analysts are more likely to downgrade stocks and lower target prices than their male counterparts, and that investors react significantly to female analysts' negative tones when discussing E&S issues in their reports. Finally, we establish that there is a positive association between analysts discussing E&S issues in their reports and/or during calls and corporate E&S performance.

As far as we are aware, we are among the first in the literature to establish the link between analysts' research activities and their monitoring using machine learning and big data. We conclude that gender diversity among equity analysts can be an impetus for firms to adopt more environmentally and socially responsible policies and practices and that our findings offer fresh evidence on the "value versus values" debate.

Appendix
Variable definitions

All continuous variables are winsorized at the 1st and 99th percentiles. All values are reported in 2021 constant dollars.

Variable	Definition
Firm-year level	
E&S score	The average of the environmental performance score and the social performance score in a given year. The data is from Refinitiv.
E score	The environmental performance score in a given year. The data is from Refinitiv.
S score	The social performance score in a given year. The data is from Refinitiv.
Carbon emissions	Natural logarithm of one plus the sum of annual Scope 1 and Scope 2 carbon emissions (metric tons of CO_2) in a given year following Sautner et al. (2023). The data is from S&P Global Trucost.
Workplace safety-related penalties	Natural logarithm of one plus the total dollar amount of penalty incurred due to a firm's workplace safety or health violations in a given year. The data is from Violation Tracker.
Workplace safety-related cases	Natural logarithm of one plus the total number of workplace safety or health violations in a given year. The data is from Violation Tracker.
N_female	The number of female analysts who cover a firm in a given year. We determine whether an analyst is a female or not based on hand-collected information.
Analyst coverage	Natural logarithm of one plus the number of analysts covering a firm in a given year.
Total assets	Book value of total assets (in billions of dollars).
Firm size	Natural logarithm of total assets.
Tobin's Q	The sum of market value of equity and book value of debt divided by total assets.
ROA	Operating income before interest and taxes divided by total assets.
Leverage	Book value of debt divided by total assets.
SG&A	SG&A expenses divided by total assets.
Cash holdings	Cash and short-term investment divided by total assets.
Tangibility	Net property, plant, and equipment divided by total assets.
Board independence	The fraction of independent directors on a board.
CEO duality	An indicator variable that takes the value of one if a CEO is chairperson of the board in a firm, and zero otherwise.
Institutional ownership	The fraction of shares outstanding held by institutional investors, set to missing if the ratio is larger than 1.
Female more general experience	An indicator variable that takes the value of one if at least one of a firm's female analysts has general experience above the median of general experience of the other analysts (excluding the focal analyst) covering the same firm in a given year, and zero otherwise. General experience is the number of years since an analyst first appears in the I/B/E/S Detail History file following Bradley, Gokkaya, and Liu (2017).

Female more firm experience	An indicator variable that takes the value of one if at least one of a firm's female analysts has firm-specific experience above the median of firm-specific experience of the other analysts (excluding the focal analyst) covering the same firm in a given year, and zero otherwise. Firm experience is the number of years since an analyst first makes an earnings forecast of the focal firm in a given year in the I/B/E/S Detail History file following Bradley, Gokkaya, and Liu (2017).
Female star analyst	An indicator variable that takes the value of one if at least one of a firm's female analysts has the Institutional Investor All-Star status in a given year, and zero otherwise.
Having female analyst	An indicator variable that takes the value of one if there is at least one female analyst who covers a firm in a given year, and zero otherwise.
Female analyst ratio	The ratio of the number of female analysts to the total number of analysts covering a firm in a given year.
N_female_Top10	The number of female analysts, from one of the top 10 brokers, who cover a firm in a given year. We determine whether a broker is one of the top 10 brokers based on size, i.e., the number of analysts from a broker who make forecasts in a given year in the I/B/E/S Detail History file.
N_female_non-Top10	The number of female analysts, not from one of the top 10 brokers, who cover a firm in a given year.
Female relative general experience	The ratio of the average general experience of female analysts covering a firm to that of male analysts covering the same firm in a given year.
Female relative firm experience	The ratio of the average firm-specific experience of female analysts covering a firm to that of male analysts covering the same firm in a given year.
Ln(1 + SG&A expenses)	Natural logarithm of one plus the SG&A expenses (in millions of dollars).
SRI fund ownership	The faction of shares outstanding held by socially responsible investment (SRI) funds. The data is from Heath et al. (2023).
G score	The governance performance score in a given year. The data is from Refinitiv.
Ln(1 + N_E&S incidents)	Natural logarithm of one plus the number of negative E&S-related news items in a given year. The data is from RepRisk.
Ln(1 + N_E incidents)	Natural logarithm of one plus the number of negative environmental-related news items in a given year. The data is from RepRisk.
Ln(1 + N_S incidents)	Natural logarithm of one plus the number of negative social-related news items in a given year. The data is from RepRisk.
Ln(1 + N_E&S sentences)	Natural logarithm of one plus the average number of E&S-related sentences in reports written by analysts covering a firm in a given year.
Ln(1 + N_E sentences)	Natural logarithm of one plus the average number of environmental-related sentences in reports written by analysts covering a firm in a given year.
Ln(1 + N_S sentences)	Natural logarithm of one plus the average number of social-related sentences in reports written by analysts covering a firm in a given year.
Ln(1 + N_E&S questions)	Natural logarithm of one plus the average number of E&S-related questions raised by analysts during a firm's conference calls in a given year.
Ln(1 + N_E questions)	Natural logarithm of one plus the average number of environmental-related questions raised by analysts during a firm's conference calls in a given year.
Ln(1 + N_S questions)	Natural logarithm of one plus the average number of social-related questions raised by analysts during a firm's conference calls in a given year.
N_female directors	The number of female directors on a firm's board in a given year.
N_female executives	The number of female executives of a firm in a given year.

Analyst report level

Having E&S sentences	An indicator variable that takes the value of one if there is at least one E&S-related sentence in an analyst report, and zero otherwise.
Having E sentences	An indicator variable that takes the value of one if there is at least one environmental-related sentence in an analyst report, and zero otherwise.
Having S sentences	An indicator variable that takes the value of one if there is at least one social-related sentence in an analyst report, and zero otherwise.
Ln(1 + N_E&S sentences)	Natural logarithm of one plus the number of E&S-related sentences in an analyst report.
Ln(1 + N_E sentences)	Natural logarithm of one plus the number of environmental-related sentences in an analyst report.
Ln(1 + N_S sentences)	Natural logarithm of one plus the number of social-related sentences in an analyst report.
Recommendation down	An indicator variable that takes the value of one if the stock recommendation in a report is revised downward compared to the last recommendation in I/B/E/S issued by the same analyst for the same firm, and zero if it is revised upward. Stock recommendation in a report uses a five-tier rating system where 2 represents "strong buy," 1 represents "buy," 0 represents "hold," -1 represents "underperform," and -2 represents "sell." To identify a revision, following Huang, Zang, and Zheng (2014, Figure 2), we first match a report to its corresponding I/B/E/S recommendation. A recommendation is considered valid during the period from the I/B/E/S announcement date until the I/B/E/S review date (i.e., when I/B/E/S confirms this recommendation is accurate). We classify a recommendation as revised if the report date is within the window from two days before to two days after the I/B/E/S announcement date, and a recommendation as reiterated if the report date is within the window from two days after the I/B/E/S announcement date to two days after the I/B/E/S review date.
Target price down	An indicator variable that takes the value of one if the target price in a report is revised downward compared to the last target price in I/B/E/S issued by the same analyst for the same firm, and zero if it is revised upward. We identify a revision following Huang, Zang, and Zheng (2014, Figure 2).
Earnings forecast down	An indicator variable that takes the value of one if the earnings forecast in a report is revised downward compared to the last earnings forecast in I/B/E/S issued by the same analyst for the same firm, and zero if it is revised upward. We identify a revision following Huang, Zang, and Zheng (2014, Figure 2).
CAR[-1,+1]	Cumulative three-day abnormal return (in percentage points) centered around the report date (day 0) based on a market model in which the market portfolio is the CRSP value-weighted market index.
Negative E&S tone	The negative value of the average tone of E&S-related sentences in an analyst report. Negative E (S) tone is defined analogously.
Negative non-E&S tone	The negative value of the average tone of non-E&S-related sentences in an analyst report.
Female	An indicator variable that takes the value of one if the lead analyst on an analyst report is a female, and zero otherwise.
Report length	Natural logarithm of the number of sentences in a report.
Recommendation revision	Recommendation in a report minus the last recommendation in I/B/E/S issued by the same analyst for the same firm following Huang, Zang, and Zheng (2014).
Target price revision	Target price in a report minus the last target price in I/B/E/S issued by the same analyst for the same firm, divided by the stock price 50 days before the report date following Huang, Zang, and Zheng (2014).

Earnings forecast revision	Earnings forecast in a report minus the last earnings forecast in I/B/E/S issued by the same analyst for the same firm, divided by the stock price 50 days before the report date following Huang, Zang, and Zheng (2014).
Prior CAR	Cumulative ten-day abnormal return (in percentage points) ending two trading days before the report date based on a market model in which the market portfolio is the CRSP value-weighted market index.
Analyst-call level	
Having E&S questions	An indicator variable that takes the value of one if an analyst raises at least one E&S-related question during a firm's earnings conference call, and zero otherwise.
Having E questions	An indicator variable that takes the value of one if an analyst raises at least one environmental-related question during a firm's earnings conference call, and zero otherwise.
Having S questions	An indicator variable that takes the value of one if an analyst raises at least one social-related question during a firm's earnings conference call, and zero otherwise.
Ln(1 + N_E&S questions)	Natural logarithm of one plus the number of E&S-related questions by an analyst during a firm's earnings conference call.
Ln(1 + N_E questions)	Natural logarithm of one plus the number of environmental-related questions by an analyst during a firm's earnings conference call.
Ln(1 + N_S questions)	Natural logarithm of one plus the number of social-related questions by an analyst during a firm's earnings conference call.
N_questions	The number of questions by an analyst during a firm's earnings conference call.
Female	An indicator variable that takes the value of one if an analyst who raises at least one question during a firm's earnings conference call is a female, and zero otherwise.
Analyst-year level	
Education	An analyst's highest degree where 1 represents a bachelor's degree, 2 represents a master's degree, 3 represents a PhD, and 0 represents degrees below a bachelor's degree (such as a high school diploma).
CFA	An indicator variable that takes the value of one if an analyst is a Chartered Financial Analyst (CFA) charter-holder, and zero otherwise.
Star analyst	An indicator variable that takes the value of one if an analyst is accredited to All-Star status, and zero otherwise.
# firms followed	Number of firms for which an analyst makes at least one forecast in a given year.
# industries followed	Number of two-digit SIC industries for which an analyst makes at least one forecast in a given year.
General experience	Number of years since an analyst first appears in the I/B/E/S Detail History file following Bradley, Gokkaya, and Liu (2017).
Analyst-firm-year level	
Forecast accuracy	The negative value of the average of the absolute forecast error made by an analyst in a given year demeaned by the average absolute forecast error of all analysts covering the same firm in the same year (Clement 1999). The absolute forecast error is the absolute value of the difference between an analyst's annual EPS forecast and the actual EPS using the I/B/E/S Unadjusted Detail file.
Forecast frequency	Number of forecasts that an analyst makes of a firm in a given year.
Forecast horizon	The average of forecast horizons (in terms of the number of days between the forecast date and the earnings announcement date) that an analyst employs when making forecasts in a firm-year.
Ln(1 + N_E&S sentences)	Natural logarithm of one plus the average number of E&S-related sentences among the reports written by an analyst covering a firm in a given year.

Ln(1 + N_E sentences)	Natural logarithm of one plus the average number of environmental-related sentences among the reports written by an analyst covering a firm in a given year.
Ln(1 + N_S sentences)	Natural logarithm of one plus the average number of social-related sentences among the reports written by an analyst covering a firm in a given year.
Ln(1 + N_E&S questions)	Natural logarithm of one plus the average number of E&S-related questions raised by an analyst during a firm's conference calls in a given year.
Ln(1 + N_E questions)	Natural logarithm of one plus the average number of environmental-related questions raised by an analyst during a firm's conference calls in a given year.
Ln(1 + N_S questions)	Natural logarithm of one plus the average number of social-related questions raised by an analyst during a firm's conference calls in a given year.

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Table 1
Sample formation

This table reports the impact of various data matching steps and data filters on sample formation. Our sample starts from Refinitiv's ESG database over the period 2005–2021.

	# firm-year obs.	# firm-year obs. removed	# unique firms
Firm-year observations in Refinitiv's ESG database over the period 2005–2021	31,800		5,054
Remove observations with missing financial information from Compustat	25,019	6,781	4,074
Remove observations with missing corporate board information from BoardEx	22,732	2,287	3,725
Remove observations with missing institutional ownership data from WRDS	20,423	2,309	3,567
Final sample	**20,423**		**3,567**

Table 2
Summary statistics

This table presents the summary statistics of our main sample. The sample consists of 20,423 firm-year observations (representing 3,567 unique firms) with data on corporate E&S performance over the period 2005–2021.

	Mean	5^{th} Percentile	Median	95^{th} Percentile	SD
E&S score	0.420	0.098	0.325	0.918	0.287
E score	0.412	0.098	0.281	0.937	0.312
S score	0.427	0.077	0.355	0.922	0.291
Carbon emissions (raw)	1,033,876	0.000	35,502	3,690,003	6,209,296
Workplace safety-related penalties (raw)	9,741	0.000	0.000	31,573	111,527
Workplace safety-related cases (raw)	0.526	0.000	0.000	2.000	5.370
Carbon emissions	8.645	0.000	10.477	15.121	5.223
Workplace safety-related penalties	1.518	0.000	0.000	10.360	3.621
Workplace safety-related cases	0.166	0.000	0.000	1.099	0.461
N_female	0.480	0.000	0.000	2.000	0.856
Having female analyst	0.310	0.000	0.000	1.000	0.463
Female analyst ratio	0.073	0.000	0.000	0.375	0.138
Analyst coverage	1.245	0.000	1.386	2.708	0.983
Total assets	16,965	157.87	3,572.3	64,607	49,742
Firm size	8.162	5.068	8.181	11.076	1.784
Tobin's Q	2.078	0.930	1.566	5.164	1.510
ROA	0.058	-0.197	0.072	0.258	0.172
Leverage	0.249	0.000	0.219	0.628	0.204
SG&A	0.215	0.010	0.132	0.713	0.255
Cash holdings	0.189	0.006	0.087	0.685	0.288
Tangibility	0.268	0.001	0.154	0.892	0.295
Board independence	0.766	0.556	0.800	0.917	0.123
CEO duality	0.405	0.000	0.000	1.000	0.491
Institutional ownership	0.643	0.009	0.735	0.965	0.289

Table 3
Female analysts and corporate E&S performance

This table presents the baseline regression estimates of the relation between female analyst coverage (*N_female*) and firms' E&S performance. Panel A examines the relation between female analyst coverage and firms' E&S performance: *E&S score, E score,* and *S score*. Panel B examines the relation between female analyst coverage and real E&S outcomes: *Caron emissions*, *Workplace safety-related penalties*, and *Workplace safety-related cases*. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Female analysts and corporate E&S performance

	E&S score	E score	S score
Variable	(1)	(2)	(3)
N_female	0.014***	0.017***	0.010***
	(0.004)	(0.004)	(0.004)
Analyst coverage	-0.011**	-0.012**	-0.011**
	(0.005)	(0.005)	(0.005)
Firm size	0.125***	0.128***	0.122***
	(0.003)	(0.003)	(0.003)
Tobin's Q	0.011***	0.011***	0.012***
	(0.002)	(0.002)	(0.002)
ROA	0.057***	0.018	0.096***
	(0.018)	(0.019)	(0.019)
Leverage	-0.070***	-0.067***	-0.074***
	(0.017)	(0.018)	(0.018)
SG&A	0.131***	0.130***	0.133***
	(0.018)	(0.020)	(0.019)
Cash holdings	-0.062***	-0.049***	-0.074***
	(0.012)	(0.013)	(0.012)
Tangibility	-0.010	0.006	-0.026
	(0.015)	(0.017)	(0.016)
Board independence	0.007	-0.008	0.022
	(0.032)	(0.036)	(0.032)
CEO duality	-0.013**	-0.012*	-0.015**
	(0.006)	(0.007)	(0.006)
Institutional ownership	-0.023**	-0.040***	-0.007
	(0.012)	(0.014)	(0.012)
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.522	0.514
No. of observations	20,423	20,423	20,423

Panel B: Female analysts and real E&S outcomes

	Carbon emissions	Workplace safety-related penalties	Workplace safety-related cases
Variable	(1)	(2)	(3)
N_female	-0.124**	-0.019***	-0.117**
	(0.059)	(0.006)	(0.049)
Analyst coverage	1.659***	0.039***	0.303***
	(0.122)	(0.008)	(0.062)
Firm size	0.782***	0.062***	0.522***
	(0.065)	(0.006)	(0.041)
Tobin's Q	-0.092**	-0.003	-0.008

	(0.040)	(0.003)	(0.025)
ROA	1.742***	-0.070***	-0.599***
	(0.351)	(0.027)	(0.219)
Leverage	0.650*	0.003	-0.010
	(0.339)	(0.027)	(0.218)
SG&A	1.221***	-0.086***	-0.802***
	(0.320)	(0.014)	(0.119)
Cash holdings	-1.433***	0.126***	0.952***
	(0.205)	(0.030)	(0.234)
Tangibility	0.161	0.034	0.273
	(0.326)	(0.028)	(0.227)
Board independence	-6.526***	-0.125**	-0.969**
	(0.621)	(0.048)	(0.384)
CEO duality	0.343***	0.033***	0.286***
	(0.116)	(0.011)	(0.082)
Institutional ownership	4.068***	0.045**	0.414**
	(0.272)	(0.021)	(0.166)
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.526	0.246	0.242
No. of observations	20,423	20,423	20,423

Table 4
Female analysts and corporate E&S performance: A DID approach

This table examines the relation between female analyst coverage and firms' E&S performance using broker closures as a quasi-natural experiment and a DID approach. *Treated* is an indicator variable that takes the value of one if a firm experiences an exogenous drop only in female analyst coverage due to broker closures, and zero otherwise. *Post* is an indicator variable that takes the value of one in the year after a broker's closure (*t+1*), and zero in the year before (*t-1*). Panel A examines the effect of broker closures on female analyst coverage. Panel B examines the effect of a drop only in female analyst coverage due to broker closures on corporate ESG performance. The sample consists of 2,604 firm-year observations (210 treated firm-year and 2,394 control firm-year observations). Panel C examines the effect of a drop only in female analyst coverage due to broker closures on real E&S outcomes. In column (1), the sample consists of 2,146 firm-year observations (204 treated firm-year and 1,942 control firm-year observations). In columns (2) and (3), the sample consists of 7,978 firm-year observations (276 treated firm-year and 7,702 control firm-year observations). Other control variables are the same as those in Panel B and are omitted for brevity. Panel D conducts a placebo test examining the effect of a drop only in male analyst coverage due to broker closures on corporate E&S performance. The sample consists of 4,026 firm-year observations (1,632 treated firm-year and 2,394 control firm-year observations). *Treated* is an indicator variable that takes the value of one if a firm experiences an exogenous drop only in male analyst coverage due to broker closures, and zero otherwise. Other control variables are the same as those in Panel B and are omitted for brevity. Panel E examines the relation between an exogenous drop in female analyst coverage and subsequent E&S incidents. Other control variables are the same as those in Panel B and are omitted for brevity. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Broker closures and female analyst coverage

Variable	N_female
Treated × Post	-0.325**
	(0.144)
Post	0.318***
	(0.041)
Constant	YES
Firm FE	YES
Year FE	YES
Adjusted R^2	0.791
No. of observations	2,604

Panel B: Broker closures, female analyst coverage, and corporate ESG performance

	E&S score	E score	S score	G score
Variable	(1)	(2)	(3)	(4)
Treated × Post	-0.024**	-0.023*	-0.025*	-0.013
	(0.012)	(0.014)	(0.015)	(0.014)
Post	0.009	0.009	0.010	0.014**
	(0.006)	(0.007)	(0.007)	(0.005)
Analyst coverage	0.022*	0.020	0.025	-0.0002
	(0.013)	(0.015)	(0.018)	(0.015)
Firm size	0.055**	0.033	0.076***	0.020
	(0.023)	(0.028)	(0.026)	(0.020)
Tobin's Q	0.003	0.002	0.004	0.002
	(0.005)	(0.006)	(0.006)	(0.007)
ROA	-0.054	-0.092	-0.016	0.132*
	(0.067)	(0.079)	(0.077)	(0.072)
Leverage	-0.127*	-0.148	-0.106	0.006
	(0.077)	(0.106)	(0.083)	(0.075)
SG&A	-0.041	-0.080	-0.002	0.006
	(0.081)	(0.097)	(0.078)	(0.081)

Cash holdings	-0.002	-0.001	-0.004	-0.012
	(0.013)	(0.016)	(0.015)	(0.016)
Tangibility	-0.016	0.035	-0.067	-0.058
	(0.068)	(0.081)	(0.076)	(0.063)
Board independence	-0.083	-0.154	-0.012	-0.081
	(0.125)	(0.121)	(0.150)	(0.096)
CEO duality	-0.037*	-0.037*	-0.036	0.006
	(0.022)	(0.021)	(0.026)	(0.014)
Institutional ownership	0.032	-0.075	0.138***	0.116***
	(0.053)	(0.080)	(0.052)	(0.040)
Constant	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adjusted R^2	0.916	0.901	0.895	0.761
No. of observations	2,604	2,604	2,604	2,604

Panel C: Broker closures, female analyst coverage, and real E&S outcomes

Variable	Carbon emissions (1)	Workplace safety-related penalties (2)	Workplace safety-related cases (3)
Treated × Post	0.253*	0.915**	0.088**
	(0.153)	(0.431)	(0.044)
Post	-0.104	-0.193	-0.015
	(0.066)	(0.190)	(0.020)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R^2	0.935	0.657	0.752
No. of observations	2,146	7,978	7,978

Panel D: Broker closures, male analyst coverage, and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
Treated × Post	-0.002	0.001	-0.005
	(0.005)	(0.006)	(0.006)
Post	0.011***	0.005	0.017***
	(0.003)	(0.004)	(0.004)
Constant	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R^2	0.923	0.906	0.887
No. of observations	4,026	4,026	4,026

Panel E: Broker closures, female analyst coverage, and negative E&S incidents

Variable	Ln(1 + N_E&S incidents) (1)	Ln(1 + N_E incidents) (2)	Ln(1 + N_S incidents) (3)
Post	-0.217	-0.073	-0.121
	(0.165)	(0.093)	(0.136)
Having E&S discussions	0.118		

	(0.333)		
Post × Having E&S discussions	0.302*		
	(0.152)		
Having E discussions		0.063	
		(0.255)	
Post × Having E discussions		0.002	
		(0.086)	
Having S discussions			-0.061
			(0.316)
Post × Having S discussions			0.287**
			(0.129)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R^2	0.372	0.469	0.335
No. of observations	210	210	210

Table 5
Female analysts and E&S discussions in analyst reports

This table examines the relation between female analyst coverage and discussions of E&S issues in analyst reports. We first download analyst reports over the period 2004–2020 from Thomson One's Investext database. We then match analyst reports with our analyst gender data set by using broker name and analyst full name. Our sample consists of 960,232 reports covering 19,274 firm-year observations (representing 1,686 unique firms). At the report level, we capture discussions of E&S issues using the fine-tuned FinBERT model to automatically classify E&S-related sentences. We employ different indicator variables (*Having E&S sentences*, *Having E sentences*, and *Having S sentences*) that take the value of one if there is at least one relevant sentence in an analyst report, and zero otherwise. We also capture the intensity of E&S discussions by using the natural logarithm of one plus the number of relevant sentences in an analyst report (*Ln(1 + N_E&S sentences)*, *Ln(1 + N_E sentences)*, and *Ln(1 + N_S sentences)*). Panel A presents the summary statistics at the report level. Panel B presents report-level regressions examining the relation between analyst gender and their E&S discussions in reports. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the analyst times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Summary statistics at the report level

	Mean	5^{th} Percentile	Median	95^{th} Percentile	SD
Having E&S sentences (× 100)	29.617	0.000	0.000	100.000	45.657
Having E sentences (× 100)	22.165	0.000	0.000	100.000	41.536
Having S sentences (× 100)	13.364	0.000	0.000	100.000	34.026
N_E&S sentences	0.917	0.000	0.000	4.000	3.344
Ln(1 + N_E&S sentences)	0.340	0.000	0.000	1.609	0.617
N_E sentences	0.644	0.000	0.000	3.000	2.799
Ln(1 + N_E sentences)	0.247	0.000	0.000	1.386	0.537
N_S sentences	0.273	0.000	0.000	1.000	1.289
Ln(1 + N_S sentences)	0.129	0.000	0.000	0.693	0.368
N_sentences	69.282	13.000	57.000	159.000	55.538
Female	0.110	0.000	0.000	1.000	0.312

Panel B: Report-level regressions examining the relation between analyst gender and E&S discussions

Variable	Having E&S sentences (× 100) (1)	Having E sentences (× 100) (2)	Having S sentences (× 100) (3)	Ln(1 + N_E&S sentences) (4)	Ln(1 + N_E sentences) (5)	Ln(1 + N_S sentences) (6)
Female	1.564***	1.027***	0.852***	0.017***	0.012***	0.006**
	(0.359)	(0.315)	(0.266)	(0.005)	(0.005)	(0.003)
Education	0.307**	0.096	0.228**	0.004*	0.001	0.004***
	(0.147)	(0.126)	(0.113)	(0.002)	(0.002)	(0.001)
CFA	-0.121	0.211	0.178	0.005	0.003	0.007***
	(0.270)	(0.238)	(0.203)	(0.004)	(0.004)	(0.002)
Star analyst	-0.502	-0.223	-0.675*	-0.008	-0.005	-0.006
	(0.474)	(0.411)	(0.345)	(0.007)	(0.005)	(0.004)
Forecast frequency	-0.358***	-0.295***	-0.254***	-0.008***	-0.006***	-0.003***
	(0.040)	(0.036)	(0.029)	(0.001)	(0.000)	(0.000)
Forecast horizon	0.007***	0.007***	0.004***	0.000***	0.000***	0.000***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
# firms followed	-0.006	0.007	-0.011	0.000	0.000	-0.000
	(0.022)	(0.021)	(0.015)	(0.000)	(0.000)	(0.000)
# industries followed	0.369***	0.326***	0.058	0.004***	0.003***	0.000
	(0.085)	(0.077)	(0.061)	(0.001)	(0.001)	(0.001)

General experience	0.009	-0.022	0.031	0.000	0.001	0.000
	(0.033)	(0.026)	(0.026)	(0.000)	(0.000)	(0.000)
Constant	YES	YES	YES	YES	YES	YES
Firm × Year FE	YES	YES	YES	YES	YES	YES
Broker × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.231	0.280	0.160	0.296	0.349	0.170
No. of observations	960,232	960,232	960,232	960,232	960,232	960,232

Table 6
Female analysts and E&S discussions during earnings conference calls

This table examines the relation between female analyst coverage and analyst raising E&S-related questions during earnings conference calls. We first download earnings call transcripts over the period 2007–2020 from Capital IQ. We then match analysts who raise questions in the Q&A section of earnings conference calls with our analyst gender data set by using broker name and analyst full name. Our sample consists of 259,801 analyst-call observations from 51,778 earnings conference calls covering 14,310 firm-year observations (representing 1,347 unique firms). At the analyst-call level, we capture E&S-related questions during a call using the fine-tuned FinBERT model to automatically classify E&S-related questions. We employ different indicator variables (*Having E&S questions*, *Having E questions*, and *Having S questions*) that take the value of one if an analyst raises at least one relevant question during a call, and zero otherwise. We also capture the intensity of E&S questions by using the natural logarithm of one plus the number of relevant questions by an analyst during a call (*Ln(1 + N_E&S questions)*, *Ln(1 + N_E questions)*, and *Ln(1 + N_S questions)*). Panel A presents the summary statistics at the analyst-call level. Panel B presents the analyst-call-level regressions examining the relation between analyst gender and their E&S-related questions during calls. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the analyst times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Summary statistics at the analyst-call level

	Mean	5th Percentile	Median	95th Percentile	SD
Having E&S questions (× 100)	15.280	0.000	0.000	100.000	35.979
Having E questions (× 100)	3.942	0.000	0.000	0.000	19.460
Having S questions (× 100)	12.017	0.000	0.000	100.000	32.516
N_E&S questions	0.183	0.000	0.000	1.000	0.472
Ln(1 + N_E&S questions)	0.118	0.000	0.000	0.693	0.285
N_E questions	0.045	0.000	0.000	0.000	0.237
Ln(1 + N_E questions)	0.030	0.000	0.000	0.000	0.149
N_S questions	0.138	0.000	0.000	1.000	0.401
Ln(1 + N_S questions)	0.090	0.000	0.000	0.693	0.250
N_questions	2.981	1.000	3.000	6.000	1.894
Female	0.118	0.000	0.000	1.000	0.322

Panel B: Analyst-call-level regressions examining the relation between analyst gender and E&S discussions

	Having E&S questions (× 100)	Having E questions (× 100)	Having S questions (× 100)	Ln(1 + N_E&S questions)	Ln(1 + N_E questions)	Ln(1 + N_S questions)
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Female	1.002***	0.208	0.729***	0.007***	0.002	0.006***
	(0.284)	(0.140)	(0.255)	(0.002)	(0.001)	(0.002)
Education	0.184	0.159**	0.084	0.002*	0.001***	0.001
	(0.121)	(0.063)	(0.108)	(0.001)	(0.000)	(0.001)
CFA	0.268	-0.092	0.370**	0.002	-0.001	0.002*
	(0.203)	(0.103)	(0.182)	(0.002)	(0.001)	(0.001)
Star analyst	0.826**	0.768***	0.301	0.006*	0.005***	0.002
	(0.408)	(0.214)	(0.353)	(0.003)	(0.002)	(0.003)
Forecast frequency	0.075*	0.035	0.046	0.001**	0.000*	0.000
	(0.040)	(0.021)	(0.035)	(0.000)	(0.000)	(0.000)
Forecast horizon	0.001	0.000	0.001	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
# firms followed	0.028	0.021**	0.012	0.000*	0.000**	0.000
	(0.017)	(0.009)	(0.016)	(0.000)	(0.000)	(0.000)

# industries followed	-0.118*	-0.042	-0.108*	-0.001*	-0.000	-0.001*
	(0.068)	(0.036)	(0.059)	(0.001)	(0.000)	(0.000)
General experience	0.124***	0.017	0.118***	0.001***	0.000*	0.001***
	(0.022)	(0.011)	(0.020)	(0.000)	(0.000)	(0.000)
	(0.284)	(0.140)	(0.255)	(0.002)	(0.001)	(0.002)
Constant	YES	YES	YES	YES	YES	YES
Firm × Year FE	YES	YES	YES	YES	YES	YES
Broker × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.094	0.135	0.089	0.109	0.150	0.103
No. of observations	259,801	259,801	259,801	259,801	259,801	259,801

Table 7
Analysts' tone in E&S-related discussions and their research output

This table examines the relation between analysts' tone in E&S-related discussions in reports and their stock recommendations, target prices, and earnings forecasts at the report level. Our sample comprises reports with recommendation/target price/earnings forecast revisions over the period 2004–2020. Panel A presents the summary statistics at the report level. Panel B presents the report-level regressions examining the relation between analyst gender, E&S-related discussions in reports, and research output. The recommendation sample consists of 50,704 reports covering 14,461 firm-year observations (representing 1,618 unique firms). The target price sample consists of 270,839 reports covering 17,714 firm-year observations (representing 1,643 unique firms). The earnings forecast sample consists of 495,115 reports covering 18,727 firm-year observations (representing 1,654 unique firms). Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the analyst time year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Summary statistics at the report level

	Mean	5^{th} Percentile	Median	95^{th} Percentile	SD
Recommendation down	0.314	0.000	0.000	1.000	0.464
Target price down	0.334	0.000	0.000	1.000	0.472
Earnings forecast down	0.445	0.000	0.000	1.000	0.497
Negative E&S tone	0.002	-0.500	0.000	0.500	0.316
Negative non-E&S Tone	0.314	0.000	0.000	1.000	0.464
Female	0.334	0.000	0.000	1.000	0.472

Panel B: Report-level regressions examining the relation between analysts' tone in E&S-related discussions and their research output

Variable	Recommendation down (1)	Target price down (2)	Earnings forecast down (3)
Female × Negative E&S tone	0.049**	0.015*	0.002
	(0.020)	(0.009)	(0.007)
Female	0.006	0.001	-0.006**
	(0.009)	(0.004)	(0.003)
Negative E&S tone	0.007	0.020***	0.009***
	(0.007)	(0.003)	(0.002)
Negative non-E&S tone	0.912***	0.732***	0.649***
	(0.015)	(0.008)	(0.006)
Report length	-0.072***	-0.025***	-0.025***
	(0.003)	(0.002)	(0.001)
Star analyst	0.035**	0.006	0.005
	(0.015)	(0.005)	(0.004)
Education	0.002	0.001	0.001
	(0.003)	(0.001)	(0.001)
CFA	0.009	-0.003	-0.005***
	(0.006)	(0.002)	(0.002)
Forecast frequency	0.012***	0.004***	0.004***
	(0.001)	(0.000)	(0.000)
Forecast horizon	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
# firms followed	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
# industries followed	0.003*	0.000	0.001**
	(0.002)	(0.001)	(0.001)
General experience	0.008***	0.001***	0.002***

	(0.001)	(0.000)	(0.000)
Constant	YES	YES	YES
Firm × Year FE	YES	YES	YES
Broker × Year FE	YES	YES	YES
Adjusted R^2	0.295	0.335	0.259
No. of observations	50,704	270,839	495,115

Table 8
Information content of analysts' E&S-related discussions in reports

This table examines the information content of analysts' E&S-related discussions at the report level. The sample comprises reports that contain an earnings forecast revision and are not issued at the same time as other reports on the same firm or as any other major corporate announcements over the period 2004–2020. Our sample consists of 27,165 reports covering 9,737 firm-year observations (representing 1,451 unique firms). Panel A presents the summary statistics for the key variables. Panel B presents the regression results. Industry fixed effects are based on Fama-French 12-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are double-clustered at the firm and analyst levels. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Summary statistics for the key variables

	Mean	5^{th} Percentile	Median	95^{th} Percentile	SD
CAR[-1,+1] (%)	0.004	-6.147	-0.021	6.249	3.853
Negative E&S tone	0.012	-1.000	0.000	1.000	0.367
Negative non-E&S tone	-0.058	-0.386	-0.044	0.243	0.193
Female	0.087	0.000	0.000	1.000	0.282

Panel B: Price reactions to analyst reports

	CAR[-1,+1]	CAR[-1,+1]
Variable	(1)	(2)
Female × Negative E&S tone	-0.541**	
	(0.238)	
Female × Negative E tone		-0.423*
		(0.229)
Female × Negative S tone		-0.300
		(0.439)
Female	0.025	0.022
	(0.089)	(0.088)
Negative E&S tone	-0.030	
	(0.074)	
Negative E tone		0.037
		(0.084)
Negative S tone		-0.173
		(0.109)
Negative non-E&S tone	-2.786***	-2.785***
	(0.158)	(0.159)
Report length	0.122***	0.122***
	(0.031)	(0.031)
Recommendation revision	0.243***	0.243***
	(0.022)	(0.022)
Target price revision	0.003**	0.003**
	(0.001)	(0.001)
Earnings forecast revision	0.135	0.131
	(0.396)	(0.396)
Prior CAR	-0.003	-0.003
	(0.005)	(0.005)
Other analyst/firm controls	YES	YES
Constant	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Adjusted R^2	0.036	0.036
No. of observations	27,165	27,165

Internet Appendix for
"Female Equity Analysts and Corporate Environmental and Social Performance"

Appendix IA
Fine-tuning FinBERT Using Active Learning

To capture analyst monitoring through their equity research and access to management, we apply novel machine learning techniques to 2,434,739 analyst reports and 129,302 earnings conference calls. Specifically, we employ active learning, a human-in-the-loop machine learning approach, to develop two domain-specific E&S text classification models to capture analysts' writing (in analyst reports) and questions (during earnings conference calls) about corporate E&S performance.

1. Preprocessing analyst reports and earnings calls

We download 2,434,739 reports over the period 2004-2020 from Thomson One's Investext database. The reports are in PDF format. We use GROBID (https://github.com/kermitt2/grobid), an open-source software, to extract structured information from PDF documents and transform this information into XML documents. The XML documents are then stripped of information identified as tables, annexes, notes, and author information; the main content is converted to plain text. We further split text into sentences using OpenNLP's sentence segment module, a built-in function in GROBID.

We download 129,302 earnings call transcripts over the period 2007-2020 from Capital IQ's Transcripts database. Given that E&S-related questions raised by an analyst during calls often involve multiple sentences, we opt to use an entire question as the unit of analysis for earnings conference call transcripts. This approach helps preserve valuable contextual information that would be lost through sentence-level analysis.

We hereafter refer to a sentence in analyst reports or a question in earnings conference call transcripts as a *passage* of text.

2. FinBERT: An introduction

Our approach builds on FinBERT (Huang, Wang, and Yang 2023), a state-of-the-art large language model pre-trained on financial text. The FinBERT model is based on the same transformer architecture of BERT (Devlin et al. 2019), a pre-trained language model that has achieved impressive results on a wide range of NLP tasks. The transformer architecture consists of multiple layers of self-attention mechanisms and feed-forward neural networks. This architecture improves the model's ability to capture long-range dependencies between words in text and facilitates more efficient parallel computations, resulting in better performance than conventional neural network-based models.

The BERT model is pre-trained on a large corpus of text, in which it learns from two tasks that can be constructed from the corpus. The first task is masked language modeling. In this task, the model predicts the identity of words that have been randomly replaced with a mask symbol (e.g., [MASK]) in a sentence. This task is designed to help the model learn the meaning of individual words and how they fit into the context of a sentence. The second task is next sentence prediction. In this task, the model is trained with a training data set in which half of the times sentence B is the actual sentence that follows sentence A, and the other half of the times B is a randomly chosen sentence from the corpus. This task helps the model learn the larger document context and better understand the relationships between different sentences in the document.

The key difference between the BERT and FinBERT models is the training data used for pre-training. While BERT is trained on general corpora, such as books and Wikipedia, FinBERT is trained on a specialized collection of financial text, including annual and quarterly reports, analyst reports, and earnings conference calls. These domain-specific training corpora allow FinBERT to better capture the unique language and terminology used in the financial domain.

After pre-training, the BERT (FinBERT) model can generate a contextualized embedding vector for each sentence, which can be further fine-tuned and used as classification features for other tasks, such as text classification. Because the model learns semantic (e.g., the meanings of words) and syntactic (e.g., the phrases and the compositions of sentences) information from a large corpus in the pre-training step, Huang, Wang, and Yang (2023) show that the fine-tuning step requires only a relatively small training sample to achieve a high accuracy of text classification. Their experiments also demonstrate that for domain-specific tasks, such as financial text sentiment classification, the FinBERT model outperforms the generic BERT model.

3. Constructing domain-specific training examples via active learning

Our goal is to train a three-class classifier that can take a passage of text, from either reports or calls, as input, and predict its probability of pertaining to environmental issues (E), social issues (S), or neither (Non-E&S).

To fine-tune the FinBERT model of Huang, Wang, and Yang (2023) using our two corpora, we employ *active learning*, a human-in-the-loop machine learning approach, to find domain-specific training examples. We then use these domain-specific training examples to fine-tune two different E&S classification models, one for analyst reports and the other for earnings conference calls.

Figure IA1 presents a flowchart of the active learning process. In Step 1, we use keywords related to E&S issues to generate a set of initial training examples. Passages containing these keywords are tentatively labeled as positive examples (E or S), and random passages are used as negative examples (Non-E&S). In Step 2, we use these initial training data to fine-tune the FinBERT model into a *Noisy E&S model*. In Step 3, we use the *Noisy E&S model* to classify the initial training examples. Given the *Noisy E&S model*'s output, a subset of important examples is labeled by human annotators. In Step 4, we use these labeled examples to fine-tune the *Noisy E&S model* and produce the *Final E&S model* (Cormack and Grossman 2014). We describe the four steps in detail below.

Step 1. Constructing the initial training data sets

In Step 1, we search for relevant passages from reports and calls on corporate E&S practices using a keyword list. To build our keyword list of corporate E&S performance, we start with one of the earliest ESG databases – the RiskMetrics KLD database (before it was acquired by MSCI and its methodology was updated). The KLD User Guide in 2010 includes descriptions of different E&S practices. The keyword list captures the essence of each broadly defined E&S category.

To search for relevant passages pertaining to E&S practices, we develop search queries to return results that match the keywords, while excluding queries that are too broad. We employ Apache Solr (https://solr.apache.org/) to index the full text and to conduct the search. Apache Solr is an open-source search platform that allows for powerful full-text search using queries that support exact term matching, the wildcard operator (e.g., the * operator represents unknown characters), and Boolean logic (e.g., AND/OR operators). For example, we drop the keyword "environment" as it is more often used to describe the macro-economic environment that is not directly related to E&S. As another example, under the E&S practices regarding product, "product recall" is a keyword. We develop the query "product* & recall," such that 1) the query identifies passages that not only match the exact phrase "product recall," but also capture sentences that include the two words separately, such as "the firm initiated a voluntary recall of some potentially contaminated products;" and 2) the query excludes irrelevant passages that only contain "recall," such as "we're generating unusually high recall rates for advertisers' brands and unusually high recall rates for advertisers' messages."

Table IA3 in the Internet Appendix lists queries of corporate E&S practices.

Using these queries, we are able to find representative in-domain passages that are likely to be related to E&S issues with minimal human intervention. For analyst reports, we find 19,555 E-related and 4,817 S-related sentences. For earnings conference calls, we find 1,201 E-related and 123 S-related questions. To construct the initial training data set for each corpus, it is also necessary to include Non-E&S examples. To do this, we randomly select an additional 20,000 passages that did not match any E or S queries for each corpus, to serve as Non-E&S examples.

Step 2. Fine-tuning FinBERT into a Noisy E&S model

In Step 2, we use the initial training sample, including both the E&S and Non-E&S examples identified in Step 1, to fine-tune the pre-trained FinBERT model into a *Noisy E&S model*. The initial training data are randomly split into 80%/10%/10% train/validation/test subsets. We use the training set to fine-tune the model, the validation set to assess the performance of the model after each epoch (i.e., an iteration of the entire training data set), and the test set to evaluate the final performance of the model. The Receiver Operating Characteristic (ROC) curve is a probability curve that plots the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings and separates the "signal" from the "noise". We use the area under the ROC curve (AUC) metric on the validation set to evaluate the performance of the model after each epoch. The training process is terminated when the AUC fails to improve after an epoch on the validation set. This approach, known as early stopping, can avoid overfitting.

The resulting model is considered a *Noisy E&S model* due to the training data containing both false negatives and false positives. Since search queries are restrictive, some negative examples (randomly drawn passages that do not match any E or S queries) in the initial training sample may be classified as relating to E or S. In addition, not all passages matching the queries in Table IA3 are definitely classified as relating to E or S.

Next, we use this *Noisy E&S model* to identify important examples for a human annotator to label.

Step 3. Identifying important examples for human annotation

In Step 3, we identify important examples for human annotation using the *Noisy E&S model*. To do this, we apply the *Noisy E&S model* from Step 2 to all examples in the initial training sample. This allows us to obtain a predicted probability vector for each example, indicating the probability that an example belongs to one of the three classes (i.e., E, S, or Non-E&S). These predicted probabilities can then be used to identify examples that are important for human annotation.

There are two common protocols for identifying important examples (Cormack and Grossman 2014). The first is continuous active learning (CAL), which entails labeling the examples that the model is most certain about (i.e., the examples with the highest predicted probabilities in either class). The second is simple active learning (SAL), which entails labeling the confusing examples that the model is unsure of (i.e., the examples with similar predicted probabilities across different classes, which can be measured using the entropy of predicted probabilities). Intuitively, when the model is trained on human-labeled examples that it has previously been most certain about, we strengthen its existing knowledge and help correct the most obvious errors, e.g., passages that match search queries but are not related to E&S given the context. On the other hand, labeling unsure examples can help the model identify the boundary between difficult cases. In the finance literature, the SAL approach is used by Kölbel et al. (2022) to construct a training sample for climate risk disclosures. Combining these two protocols allows the model to focus on the most informative examples rather than random examples in the training sample, which can improve the accuracy and efficiency of model training.

For CAL, we sort the examples based on the predicted probabilities provided by the *Noisy E&S model* and select the top 500 examples with the highest predicted probabilities belonging to E (S), resulting in 1,000 examples. For SAL, we calculate the entropy of the predicted probability vector for each example and select the top 500 examples with the highest entropy. Entropy is a measure of the uncertainty of a probability distribution, and it is calculated as the sum of $-p \times log(p)$ over all classes where p is probability. An example with P(E) = P(S) = P(Non-E&S) = 0.33 would have the highest entropy and be at the top of the SAL list. In total, the human annotators (authors of this paper) manually label 1,500 examples for each corpus.

Table IA4 in the Internet Appendix lists some important examples identified by active learning protocols (CAL and SAL), illustrating how the *Noisy E&S model*'s predictions and human labels correspond in different contexts.

Step 4. Fine-tuning the Noisy E&S model into the Final E&S model

In the final step, the human-annotated examples are used to further fine-tune the *Noisy E&S model* into the *Final E&S model*. This step follows the methodology outlined in Step 2 and is therefore omitted in the interest of brevity.

4. Choosing a classification threshold

Given a passage, our *Final E&S model* produces a continuous probability in the interval [0,1] for each of the three classes (E, S, and Non-E&S). To obtain a discrete label from these scores, we require a threshold t_c, and assign a label $C \in [E, S, Non\text{-}E\&S]$ to any passage with a predicted probability $P(C) \geq t_c$. Using discrete labels allows us to identify individual passages related to E&S issues for further analysis.

Choosing an appropriate threshold t_c requires balancing precision and recall. A low threshold will be too loose and will identify more passages as relevant that are only tangentially related to E&S, resulting in a high recall but low precision (a high false positive rate). On the other hand, a high threshold will be too strict and will identify only a small number of passages, resulting in a high precision but low recall (a high false negative rate). Picking a threshold is also necessary as our initial training sample is highly unbalanced, with the number of non-E&S examples dominating the other two classes.

To select the threshold t_c, we consult existing literature on classifying E&S issues using textual data so that the fraction of E&S passages identified by our *Final E&S model* with the chosen threshold t_c is in line with the reported values in the literature.

After removing reports from firms not included in the main sample and removing short sentences whose length falls below the bottom decile (8 words), our final sample comprises 965,377 analyst reports. For analyst reports, we set $t_E = 0.01$ and $t_S = 0.01$. After applying these thresholds, we find that the fraction of reports writing about environmental issues is 22.1%, and the fraction of reports writing about social issues is 13.4%. As far as we are aware, we are the first in the literature to examine E&S-related discussions in analyst reports; there are no comparable statistics in the literature.

After removing calls from firms not included in the main sample and removing short questions whose length falls below the bottom decile (11 words), our final sample comprises 51,872 earnings calls. For calls, we set $t_E = 0.020$, and $t_S = 0.015$. After applying these thresholds, we find that the fraction of calls discussing environmental issues is 12.4%, and the fraction of calls discussing social issues is 31.9%. These values fall within the range of the reported values in the literature whereby the fraction of calls discussing environmental issues ranges between 7% and 58%, and the fraction of calls discussing social issues ranges between 7% and 45% (Raman, Bang, and Nourbakhsh 2020; Chava, Du, and Malakar 2021).

5. Model interpretability analysis

Figure IA4 provides a model interpretability analysis to shed light on the qualitative differences between the two corpora. We utilize the integrated gradients method, a recent development in interpretability techniques for neural networks (Sundararajan, Taly, and Yan 2017). The method determines which input features – in our case, tokens in raw text – are most important in the fine-tuned FinBERT models' classification of each sentence.[1] We sample a total of 5,000 sentences from reports and 5,000 questions from calls that have been classified as either E or S and compute the importance score of the tokens. We then average the importance scores across the sample sentences and questions for each corpus, providing a corpus-specific measure of the importance of each token.

In Panel A, we show that among the E-related sentences, environmental damages and remediation-related issues (e.g., *remediation, hazardous*, *ozone*) are relatively more important in reports, whereas pollution, climate, and greenhouse-related issues (e.g., *pollution, renewables, climate, greenhouse*) are more important during calls. In Panel B, we show that among the S-related sentences, both corpora emphasize the significance of employee-related issues such as layoffs, safety, and strikes, but they diverge on broader topics. Community relations and discrimination-related issues (e.g., *community, sex, discriminations*) are given more emphasis in reports, while corporate wrongdoing (e.g., *corruption*, *indigenous, violation*), and cybersecurity incidents (e.g., *hackers*) are more important during calls. Overall, the analysis indicates that the fine-tuned FinBERT models possess high face validity for both corpora, and that the relative importance of tokens varies depending on the context. These findings support our decision to fine-tune separate machine learning models for analyst reports and earnings calls.

6. Structure topic modeling

This section provides additional details on the Structural Topic Modeling (STM) analysis used to investigate thematic differences in how male and female analysts discuss environmental and social (E&S) issues. The STM approach, developed by Roberts et al. (2014), enables the discovery of latent topics within a corpus of documents while accounting for document-level covariates such as analyst gender. We use the approach to explore how gender influences the prevalence of various E&S themes in analysts' writing and questions.

The STM approach offers several key advantages over traditional topic modeling methods like Latent Dirichlet Allocation (LDA). First, by explicitly modeling document-level covariates as variables affecting the prior distribution of topic proportions and topic-word distributions, STM allows researchers to directly estimate the relationships between metadata and topical prevalence as well as topical content. This provides a principled way to test hypotheses about the factors that drive both how much documents discuss certain topics and the language used to discuss those topics. In contrast, LDA does not incorporate covariate information into the model. Second, the inclusion of covariates in STM can significantly enhance the interpretability of topics. By identifying topics that are strongly associated with metadata attributes of interest, such as document source or author characteristics, we can gain additional context to understand the substantive meaning and significance of topics.

We apply STM using the R package *stm* (Roberts et al. 2019) to four corpora: (1) sentences in analyst reports discussing environmental issues, (2) sentences in analyst reports discussing social issues, (3) paragraphs in earnings call questions related to environmental issues, and (4) paragraphs in earnings call questions related to social issues. For each corpus, the gender of the analyst is included as a covariate. The STM is then estimated using a variational expectation-maximization algorithm until convergence. To interpret and label the discovered topics, we examine the most prevalent words and

[1] The integrated gradients method utilized in our analysis is conceptually similar to the SHAP (Shapley Additive exPlanations) method used in Erel, Stern, Tan, and Weisbach (2021). The advantage of using this method in our context is that it is computationally more efficient with differentiable models such as neural networks. Furthermore, it is well suited for cases in which the input space is high-dimensional or continuous, which is common in natural language processing tasks such as ours.

documents associated with each topic. Table IA12 presents the top words for each topic in each corpus, along with our assigned labels. These labels are based on collections of words that are strongly associated with each topic, using the score criteria which divides the log frequency of a word in a topic by its log frequency in other topics.

To assess the relationship between analyst gender and E&S topic prevalence, STM calculates differences in topic proportions for each topic between male and female analysts. This is done by first fitting the STM model with analyst gender as a covariate to obtain a posterior distribution over the topic proportions. The estimateEffect function in the *stm* package then performs posterior inference by simulating from the variational approximation and estimating the expected topic proportion for each topic when setting the gender covariate to male versus female. Figure IA6 displays the estimated difference in topic proportions between female and male analysts for each corpus, along with 95% confidence intervals. The differences are also summarized in the last column of Table IA16. Positive values indicate topics that are more prevalent among female analysts, while negative values indicate topics that are more prevalent among male analysts.

Our STM analysis reveals substantial and consistent differences in the topics emphasized by male and female analysts across all four corpora. In the context of analyst reports discussing environmental issues, we find that male analysts focus more on topics related to "Market Dynamics & Energy Sector," while female analysts place greater emphasis on "Strategic Planning & Stakeholders." The topics "Growth & Industrial Performance" and "Sales & Environmental Factors" have similar prevalence for both genders. For analyst reports discussing social issues, female analysts tend to focus more on "Regulatory Compliance" and "Employees & Risk Management," whereas male analysts prioritize "Management & Investment Strategies" and "Market Dynamics & Operational Performance."

Turning to earnings call questions, we observe a similar pattern of gender differences. In the context of environmental issues, male analysts are more likely to ask questions related to "Energy Sector & Business Growth," while female analysts tend to focus on "Cost Management & Environmental Factors" and "Market Opportunities & Capital Projects." The topic "Financial Performance & Operational Updates" has similar prevalence for both genders. When discussing social issues during earnings calls, female analysts place greater weight on topics related to "Leadership & Stakeholders" and "Sales & Brand Impacts," while male analysts prioritize "Financial Metrics & Cost Management" and "Operational Changes & Human Resources."

These findings indicate that female analysts adopt a more holistic, stakeholder-oriented perspective when discussing E&S issues, considering factors such as regulatory compliance, risk management, strategic planning, and customer impact. In contrast, male analysts tend to take a more shareholder-oriented perspective, emphasizing metrics related to profitability, efficiency, and market positioning.

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Figure IA1
Active learning flowchart

This figure presents a flowchart of the active learning process.

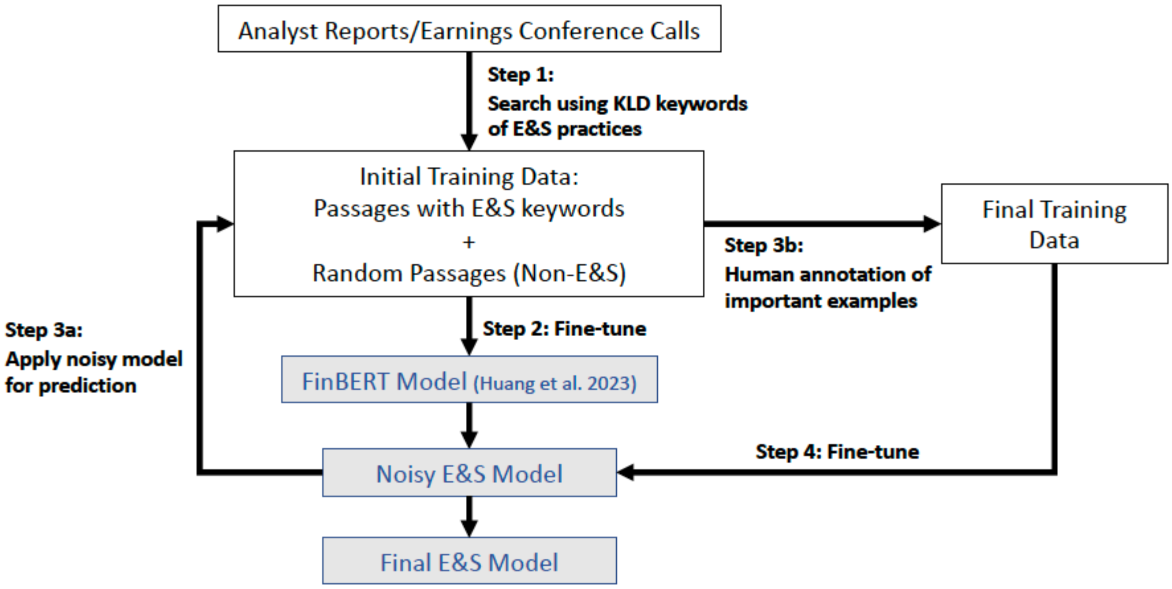


Figure IA2
Temporal trends in E&S-related discussions in analyst reports and during calls

This figure plots the temporal trend in E&S-related discussions in analyst reports and E&S-related questions during earnings conference calls. We obtain analyst reports over the period 2004–2020 from Thomson One's Investext database, and earnings call transcripts over the period 2007–2020 from Capital IQ. We capture discussions of E&S issues (E&S-related questions) using the fine-tuned FinBERT model to automatically classify E&S-related sentences (questions). We plot the yearly averages of the percentage of reports with E- or S-related sentences and the percentage of E- or S-related questions in calls.

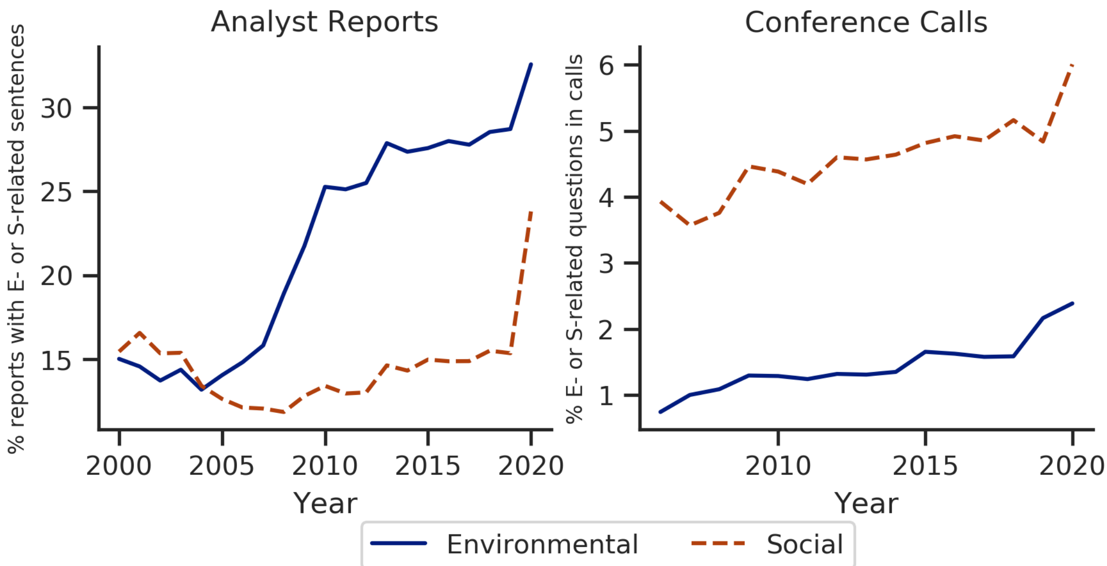


Figure IA3
Distribution of E&S-related discussions in analyst reports and during calls across Fama-French 12 industries

This figure plots the distribution of E&S-related discussions in analyst reports and E&S-related questions during earnings conference calls across Fama-French 12 industries. We obtain analyst reports over the period 2004–2020 from Thomson One's Investext database, and earnings call transcripts over the period 2007–2020 from Capital IQ. We capture discussions of E&S issues (E&S-related questions) using the fine-tuned FinBERT model to automatically classify E&S-related sentences (questions). We plot the industry averages of the percentage of reports with E- or S-related sentences and the percentage of E- or S-related questions in calls.

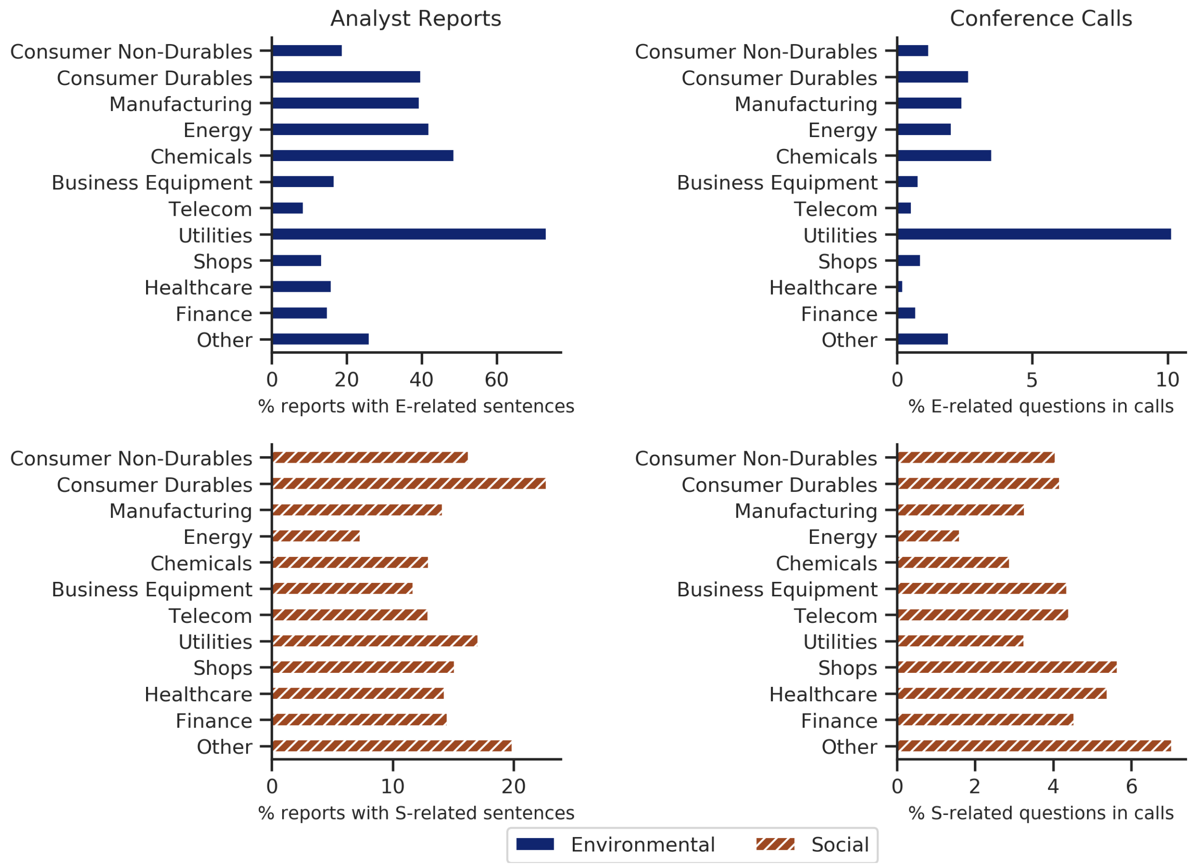
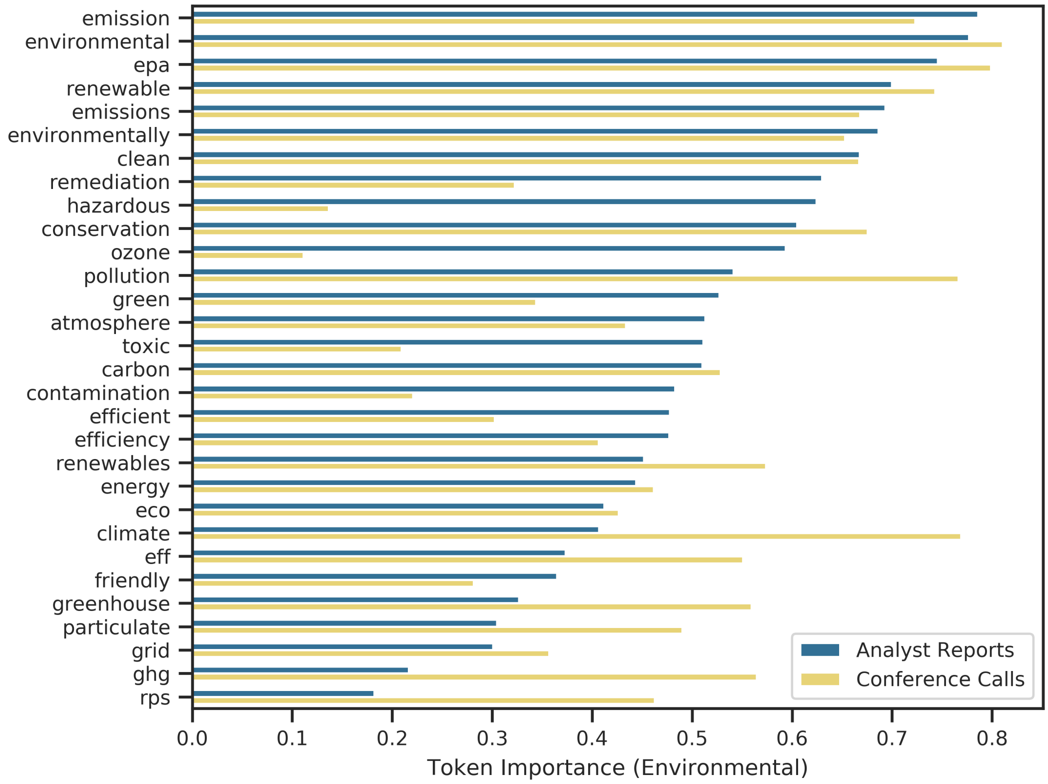


Figure IA4
Most important tokens in fine-tuned FinBERT models

This figure lists the most important tokens from our fine-tuned FinBERT models. We obtain analyst reports over the period 2004–2020 from Thomson One's Investext database, and earnings call transcripts over the period 2007–2020 from Capital IQ. We capture discussions of E&S issues (E&S-related questions) using the fine-tuned FinBERT model to automatically classify E&S-related sentences (questions). We use the integrated gradients method (Sundararajan, Taly, and Yan 2017) to compute the token importance for each corpus. The integrated gradients method is a technique for explaining the prediction of a machine learning model by attributing the importance of each token to the model's output. The FinBERT model, like many other transformer-based models, uses subword tokenization to break up words into smaller pieces (e.g., *resident* is tokenized to *re* and *##sident*).

Panel A: Most important tokens on environmental issues



Panel B: Most important tokens on social issues

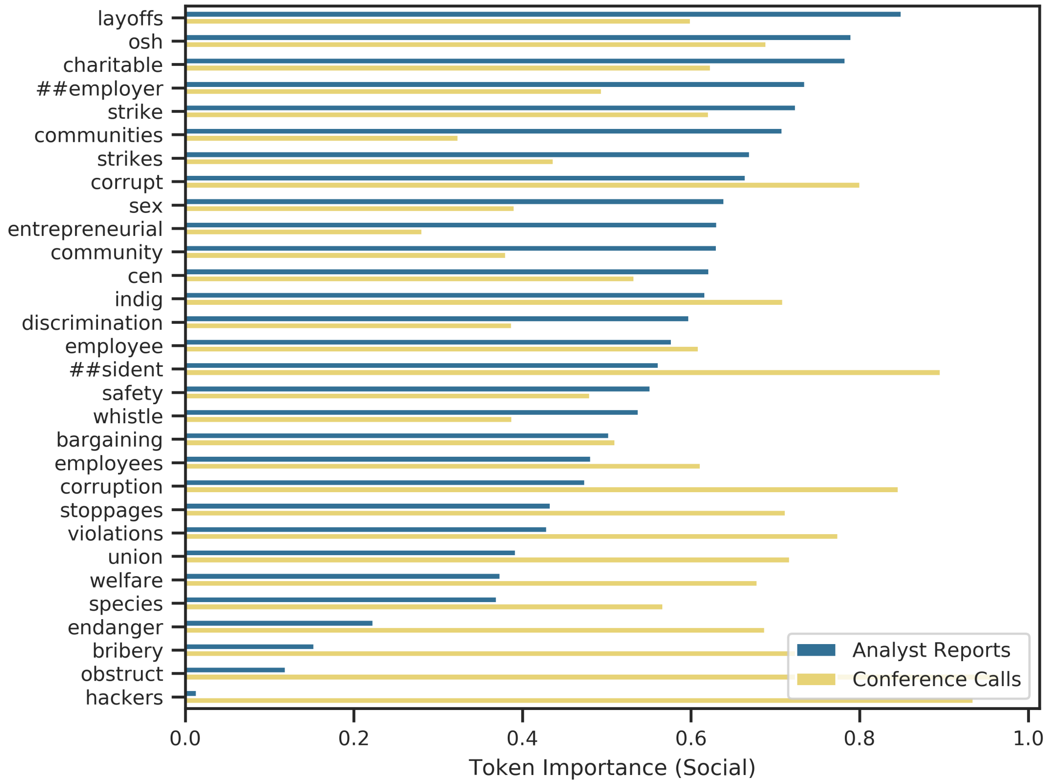


Figure IA5
Broker closures over time

This figure plots the temporal distribution of the 24 broker closures over the period 2005–2017 that result in an exogenous drop only in female analyst coverage.

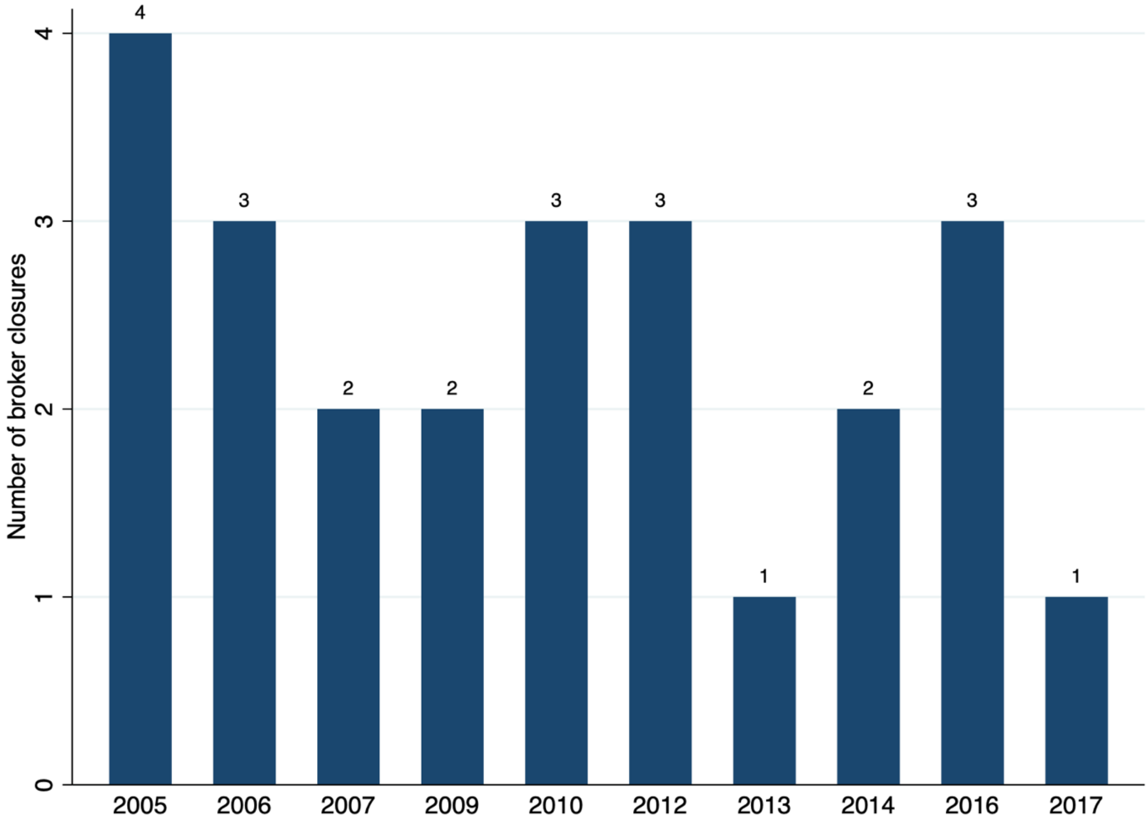


Figure IA6
Analyst gender and E&S topic prevalence

This figure displays the estimated differences in topic proportions between female and male analysts for each corpus. The horizontal bars represent the magnitude of the difference, with positive values indicating topics that are more prevalent among female analysts and negative values indicating topics that are more prevalent among male analysts. The whisker depicts the 95% confidence interval for each estimated difference. The topic labels are based on the most prevalent and distinctive words associated with each topic, as determined by the STM analysis and presented in Table IA16.

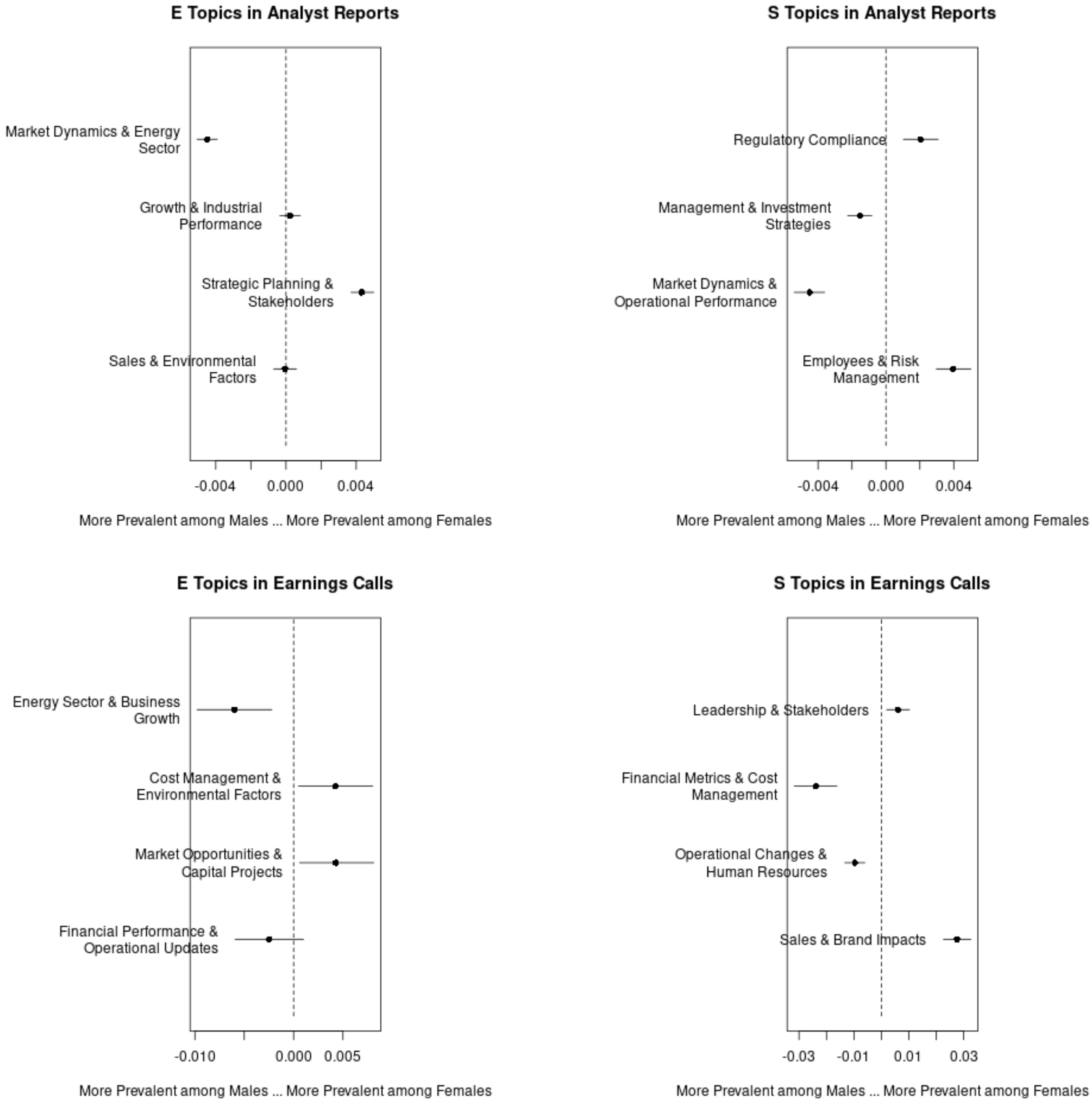


Table IA1
Female analysts over time and across Fama-French 12 industries

This table provides an overview of female analysts over time and across Fama-French 12 industries over the period 2004–2020. The sample is the I/B/E/S-Capital IQ merged sample with hand-collected gender information, as described in Section 3.2. *N_female* is the total number of female analysts present during a given time period or covering a specific industry, *N_analyst* is the total number of analysts present during a given time period or covering a specific industry, and *Female analyst ratio* is the ratio of the number of female analysts to the total number of analysts.

Panel A: Temporal trend in female analysts

	N_female	N_analyst	Female analyst ratio
2004-2007	577	4,086	0.14
2008-2011	596	4,075	0.15
2012-2015	482	3,741	0.13
2016-2020	513	3,389	0.15

Panel B: Industry distribution of female analysts

	N_female	N_analyst	Female analyst ratio
Consumer Non-Durables	223	1,056	0.21
Consumer Durables	114	842	0.14
Manufacturing	251	1,858	0.14
Energy	108	971	0.11
Chemicals	97	660	0.15
Business Equipment	378	2,952	0.13
Telecom	80	668	0.12
Utilities	76	480	0.16
Shops	369	2,107	0.18
Healthcare	263	1,437	0.18
Finance	266	2,058	0.13
Other	369	2,807	0.13

Table IA2
Correlation matrices for the firm-year sample

This table presents the correlation matrices of the firm-year sample in Table 2. Definitions of the variables are provided in the Appendix. Superscripts a, b, and c indicate significance at the 1, 5, and 10 percent levels, respectively.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. E&S score	1																
2. E score	0.957^{a}	1															
3. S score	0.951^{a}	0.821^{a}	1														
4. Carbon emissions	0.291^{a}	0.279^{a}	0.277^{a}	1													
5. Workplace safety-related penalties	0.228^{a}	0.225^{a}	0.210^{a}	0.264^{a}	1												
6. Workplace safety-related cases	0.248^{a}	0.247^{a}	0.225^{a}	0.281^{a}	0.897^{a}	1											
7. N_female	0.197^{a}	0.182^{a}	0.195^{a}	0.265^{a}	0.087^{a}	0.092^{a}	1										
8. Analyst coverage	0.217^{a}	0.197^{a}	0.218^{a}	0.430^{a}	0.149^{a}	0.144^{a}	0.562^{a}	1									
9. Firm size	0.559^{a}	0.514^{a}	0.555^{a}	0.315^{a}	0.218^{a}	0.227^{a}	0.269^{a}	0.346^{a}	1								
10. Tobin's Q	-0.072^{a}	-0.073^{a}	-0.065^{a}	-0.021^{a}	-0.061^{a}	-0.065^{a}	0.087^{a}	0.121^{a}	-0.321^{a}	1							
11. ROA	0.245^{a}	0.214^{a}	0.255^{a}	0.261^{a}	0.108^{a}	0.128^{a}	0.130^{a}	0.161^{a}	0.330^{a}	-0.052^{a}	1						
12. Leverage	0.094^{a}	0.108^{a}	0.070^{a}	0.171^{a}	0.086^{a}	0.094^{a}	-0.009	0.046^{a}	0.151^{a}	-0.099^{a}	0.067^{a}	1					
13. SG&A	-0.145^{a}	-0.134^{a}	-0.143^{a}	-0.029^{a}	-0.056^{a}	-0.058^{a}	0.066^{a}	0.059^{a}	-0.457^{a}	0.551^{a}	-0.351^{a}	-0.162^{a}	1				
14. Cash holdings	-0.177^{a}	-0.160^{a}	-0.179^{a}	-0.147^{a}	-0.125^{a}	-0.141^{a}	0.021^{a}	0.038^{a}	-0.363^{a}	0.506^{a}	-0.444^{a}	-0.251^{a}	0.591^{a}	1			
15. Tangibility	0.077^{a}	0.080^{a}	0.066^{a}	-0.013^{c}	0.151^{a}	0.135^{a}	-0.019^{a}	-0.065^{a}	0.008	-0.073^{a}	0.077^{a}	0.129^{a}	-0.136^{a}	-0.135^{a}	1		
16. Board independence	-0.205^{a}	-0.186^{a}	-0.206^{a}	-0.305^{a}	-0.121^{a}	-0.123^{a}	-0.262^{a}	-0.373^{a}	-0.278^{a}	-0.154^{a}	-0.202^{a}	0.021^{a}	-0.049^{a}	-0.029^{a}	-0.005	1	
17. CEO duality	0.062^{a}	0.057^{a}	0.062^{a}	0.164^{a}	0.083^{a}	0.092^{a}	0.114^{a}	0.176^{a}	0.153^{a}	0.039^{a}	0.065^{a}	-0.006	0.005	-0.023^{a}	-0.030^{a}	-0.201^{a}	1
18. Institutional ownership	0.142^{a}	0.125^{a}	0.147^{a}	0.462^{a}	0.101^{a}	0.125^{a}	0.176^{a}	0.412^{a}	0.148^{a}	0.052^{a}	0.228^{a}	0.076^{a}	0.028^{a}	-0.041^{a}	-0.141^{a}	-0.143^{a}	0.119^{a}

Table IA3
Queries of E&S issues

This table lists queries developed from the KLD User Guide (2010, the last version before RiskMetrics KLD was acquired by MSCI) to capture E&S issues. We apply these queries to analyst reports and earnings call transcripts to identify analysts' discussion of E&S issues. For example, a query using "*communit* & involvement*" means that only a passage includes both a word starting with *"communit"* (such as "*community*" and "*communities*") and the *"involvement"* is considered to be relevant discussions of E&S issues regarding community.

E&S practices	Queries
Community	communit* && charitable, "community involvement", "community reinvestment act" NOT "community reinvestment act funds", "disadvantaged people", "disadvantaged groups", communit* && donation, "underserved communities", "indigenous people", "local community" NOT banks NOT bank NOT "local community papers" NOT local , community pharmacy" NOT "local community hospital" NOT "merger" NOT "local community storefronts", communit* && ngo, communit* && "non-profit organizations", "socially responsible investing", "local communities" && support, "local communities" && sponsor, communit* && volunteer, communit* && youth && training
Diversity	diversity && bisexual, "black owned" NOT "national association of black owned broadcasters" NOT "orange is the new black", diversity && csr NOT market, diversity && esg, "female ceo", "female executives", diversity && gay, diversity && gender, glbt*, lgbt*, "ethnic diversity", diversity && inclusive NOT geographic, "sexual orientation", transgendered, "veteran owned", "female owned", diversity && inclusion, "work-life balance", diversity && workforce
Employee relations	"defined benefit" && underfunded, "health and safety" && employees, "no-layoff", osha NOT joe NOT "j. osha" NOT "joseph osha" NOT stericycle NOT "steri safe", employee* && "profit sharing", strike* && employee* NOT "strike me" NOT "strikes me" NOT "strikes you" NOT "strike , rice", "wrongful termination" NOT "please call us", "union relations" NOT "the company specific risks to our investment thesis include", health && safety && employee*, "significant layoffs", "significant workforce reduction", "major layoff"
Environment	environment* && "circular economy", "clean air act", "clean energy" NOT "clean energy ventures" NOT "allete clean energy" NOT "lu'an clean energy company" NOT "china sunergy co" NOT "clean energy group" NOT "s&p global clean energy index" NOT "okeechobee clean energy center" NOT "con edison clean energy businesses" NOT "clean energy fuels" NOT "global clean energy holdings", "clean water act", "climate change", "eco-friendly", "ecological restoration", "emission reduction", "energy efficient", "energy efficiency", environmental* && lawsuits, "environmental protection agency", epa && regulation*, environmental* && remediation, "environmental sustainability", "global reporting initiative", "green building", "green transport", "greenhouse gas", "gri guidelines", liabilities && hazardous, "iso 14001", "iso 50001", environment* && carbon && emission*, environment* && co2 && emission*, "carbon footprint", environment* && ozone , environment* && pollut* NOT "competitive environment", environment* && "renewable energy", environmental* && sourcing, "safe drinking water act", environmentally && sustainable, environment* && toxic
Human rights	"child labor", "forced labor", "free association", "free speech" NOT grounds, censorship, "human rights", "human trafficking", "labor rights", "prison labor"
Product	antitrust && violation, "product safety" && issues, cpsia, "food safety" && violations

Table IA4
Important training examples in active learning

This table lists examples from the two corpora (reports and calls) that are identified as important for human annotation in active learning, using Continuous Active Learning (CAL) and Simple Active Learning (SAL) protocols. CAL focuses on examples the model is most certain about, while SAL focuses on examples the model is uncertain about. For CAL-selected examples, the *Noisy E&S model*'s predicted class probabilities, along with the human labels, are provided. For SAL-selected examples, the *Noisy E&S model*'s predicted labels and the corresponding human labels are provided.

Panel A: Important examples from analyst reports

SAL (High uncertainty examples)
Example 1: Unlike other equity analysts and market commentators, our focus is on leveraging overriding themes -an approach called Thematic Investing that looks to identify emerging economic, political, regulatory and social structural changes around the globe, and then seeks to determine which companies will be impacted by it -both those that stand to benefit from the tidal wave, and those that will be drowned out by it. *Noisy E&S Model Class Probability*: P(E) = 0.53, P(S) = 0.4, P(N) = 0.4 *Human Label:* [N]
Example 2: However, in May, the Fourth Circuit vacated ACP's "incidental take" permit issued by the US Fish and Wildlife Service, meant to help protect endangered species at water crossings along the route. *Noisy E&S Model Class Probability*: P(E) = 0.81, P(S) = 0.17, P(N) = 0.02 *Human Label*: [E]
Example 3: Below we discuss the business segment results: Revenues in its Consumer and Commercial Services division increased 15% to $1 billion, reflecting strong revenue contribution from Terminix, American Home Shield (AHS), ARS/Rescue Rooter (ARS), ServiceMaster Clean and Merry Maids. *Noisy E&S Model Class Probability:* P(E) = 0.29, P(S) = 0.56, P(N) = 0.15 *Human Label*: [N]
CAL (High predicted probability examples)
Example 1: Importantly, US Ecology management reiterated its commitment to the current dividend ($0.72/share annually). *Noisy E&S Model Label:* [E] *Human Label:* [N]
Example 2: Citi Holdings net income came in lower than expected with a net loss of $802 million, driven by larger than expected losses in the Special Asset Pool segment ("SAP") as there were no recorded securities gains and lower loan balances in Local Community Lending ("LCL") which led to lower net interest revenue. *Noisy E&S Model Label*: [S] *Human Label:* [N]
Example 3: When asked about the recent performance of its Southern California division, Safeways CEO stated only that it has been consistent with other post-strike periods, though cost savings have been realized a bit earlier than expected due to a larger number of employees not returning to work upon conclusion of the strike.

Noisy E&S Model Label: [S] *Human Label*: [S]

Panel B: Important examples from earnings conference calls

SAL (High uncertainty examples)
Example 1: In the United States, a kind of a two-part question. With a modest reflation, kind of a grinding economic expansion, some tax revenues to the municipal levels going up, what are you seeing in demand from U.S. fire departments be either volunteer rural or the full-service cities, with the demand from fire suits, and then also too after 9/11. I think the Bush administration set up a number of depots for hazmat suits, first responders. You've said, Chris, over time that those, the glue in those different suits tends to erode. How do you see from kind of a national security or a homeland security, any follow up to replace some of that aging 9/11 suit stuff? *Noisy E&S Model Class Probability*: P(E) = 0.19, P(S) = 0.57, P(N) = 0.24 *Human Label*: [S]
Example 2: If somebody answered this, I can just go back and read the transcript later. But I'm just wondering if you talked at all about sort of your expectation for soy crush margins, as the Argentine farmer begins to release all these pent-up beans. Are you anticipating any sort of degradation in the crush outlook? *Noisy E&S Model Class Probability:* P(E) = 0.42, P(S) = 0.14, P(N) = 0.44 *Human Label*: [N]
Example 3: Robert, I mean, and Emanuele, clearly, this is a bold move by the company. I mean, it looks well timed. I mean today, BP just came out and announced they're going to cut oil and gas CapEx by 40% and shift that into renewables. As you thought about this pivot into offshore wind, I guess, a little -- could you give us a little bit of color around when you started thinking about it? I'm assuming you had a lot of conversations with a lot of potential customers. Kind of just could you give us some of the genesis around the decision to make this move? *Noisy E&S Model Class Probability*: P(E) = 0.46, P(S) = 0.0, P(N) = 0.54 *Human Label*: [E]
CAL (High predicted probability examples)
Example 1: Okay. Last housekeeping on the mediation with the Teamsters in Auburn. Has the union also agreed to mediation? *Noisy E&S Model Label:* [S] *Human Label*: [S]
Example 2: Okay. And also, going back to the market, there has been a great deal of publicity regarding cutbacks in spending by state and local governments due to lower tax revenues. Have you seen an impact upon your monthly run rate of orders this year so far from domestic law enforcement agencies because of it? *Noisy E&S Model Label*: [S] *Human Label*: [N]
Example 3: So the increase in nonperforming loans, it's interesting that, that is not at all energy-related or at least a majority of it is not energy-related and that is your nonenergy C&I. Can you just expand a little bit on what specifically drove that increase in 1Q? *Noisy E&S Model Label*: [E] *Human Label*: [N]

Table IA5
Examples of E&S-related sentences in analyst reports

This table lists examples of E&S-related sentences in analyst reports used in Table 5. At the report level, we capture discussions of E&S issues using the fine-tuned FinBERT model to automatically classify E&S-related sentences. Panel A lists examples of environmental-related sentences. Panel B lists examples of social-related sentences.

Panel A: Environmental-related sentences

Example 1: This report was written by Hayley Beth Wolff (Female) from Rochdale Securities LLC for Polaris Inc. released on 7/27/2009. More significantly, we believe that eco-friendly engine may satisfy the growing demand from many government agencies such as the US Forest Service and US military, looking for more environmentally friendly solutions to gas-powered vehicles.
Example 2: This report was written by David Begleiter (Male) from Deutsche Bank for Eastman Chemical Company released on 3/7/2011. Going forward Eastman has established a 10-year environmental target for 25% reduction in energy intensity, 20% reduction in greenhouse gas intensity, and 20% NO_2 & 40% SO_2 reductions.
Example 3: This report was written by Vishal Shah (Male) from Deutsche Bank for First Solar released on 9/15/2011. However, we anticipate a paradigm shift going forward, with clean electricity generation, particularly solar, gaining traction in several end-markets, supported by favorable government policies and improving cost structures.
Example 4: This report was written by Ann Kohler (Female) from Imperial Capital for Valero Energy Corp released on 1/31/2013. Although there are limited government mandated regulatory capital requirement for refiners in the near term, the federal government continues to seek to reduce refinery emissions, including greenhouse gases through increased regulations by the Environmental Protection Agency (EPA).
Example 5: This report was written by Ryan Brinkman (Male) from J.P. Morgan for Tenneco released on 8/22/2017. Tenneco management stated in our meetings that looking just at the US Tier 3 regulation alone for light vehicles, the Environmental Protection Agency (EPA) has referenced a +$72 content per vehicle cost to manufacturers in order to comply with these stricter regulations (with much of this representing revenue opportunity for Tenneco -some of the incremental content will be on the engine side, but much of it will be on the tailpipe end).

Panel B: Social-related sentences

Example 1: This report was written by Stacey Widlitz (Female) from Fulcrum Global Partners for Tiffany & CO. released on 7/1/2005. To be sure, some human rights organizations have made accusations that De Beers Group mining resulted in the relocation of bushmen in Botswana.

Example 2: This report was written by Ann Duignan (Female) from J.P. Morgan for Eaton Corp released on 9/22/2011. What was interesting about this facility was the strong sense of community -employees come in early to participate in team activities, some volunteer at the on-campus school for local, underprivileged children, and many participate in on-campus sports activities to represent "team Eaton" vs. other local companies.
Example 3: This report was written by Devina Mehra (Female) from First Global Stockbroking for Philip Morris International released on 12/23/2012. With tobacco, the main constituent of cigarettes, being the single greatest cause of preventable death globally and highly addictive, PMI's operations (as well as of its competitors) are highly controversial and are increasingly the subject of litigation and restrictive legislation from governments concerned about the health impacts of tobacco products.
Example 4: This report was written by Joseph Bonner (Male) from Argus Research for Alphabet Inc. released on 12/9/2019. Messrs. Page and Brin are leaving executive management just as Alphabet faces a daunting range of challenges: multiple antitrust investigations, both in the U.S. and abroad; intense competition for internet advertising from Facebook and Amazon; issues surrounding user privacy; YouTube's potential liabilities for endangering the welfare of children; and an increasingly restive workforce.
Example 5: This report was written by Jonathan Ho (Male) from William Blair & Company for Axon Enterprise released on 11/5/2020. Regarding gender and racial/ethnic diversity, the company's board of directors is one-third female.

Table IA6
Examples of E&S-related questions during calls

This table lists examples of E&S-related questions during earnings conference calls used in Table 6. At the analyst-call level, we capture E&S-related questions using the fine-tuned FinBERT model to automatically classify E&S-related questions. Panel A lists examples of environmental-related questions. Panel B lists examples of social-related questions.

Panel A: Environmental-related questions

Example 1: The question was asked by Marc de Croisset (Male) from FBR Capital Markets & Co. on the FQ2 2011 earnings conference call of The Southern Company held on 07/27/2011. If I may, I'd love to ask a quick question on your thoughts on the Cross State Air Pollution Rule. One of the arguments that I think the EPA has made is that SO2 compliance could be achieved by having utilities use existing scrubbers more effectively, and as a result, that would be one of the means to reduce -- to achieve SO2 compliance. And I'd be very interested in your reaction to this argument. And have you seen any indication in the industry that -- or in your region, that scrubbers, over the last several years, may not have been utilized as often or as effectively as they could be?
Example 2: The question was asked by Ryan J. Brinkman (Male) from KeyBanc Capital Markets Inc. on the FQ3 2015 earnings conference call of Tesla, Inc. held on 03/11/2015. Just maybe going back to the Dieselgate issue again, but from a bigger picture perspective. I'm curious what impact you see to the electric vehicle market from these revelations at VW. Could it increase the demand for electric vehicles to your benefit? Does it maybe make nonelectric vehicles more expensive to produce to truly comply with the emission regulations? Does that help the Model 3 be more cost- competitive? I'm just curious what impact you see overall to the industry, and then to Tesla specifically.
Example 3: The question was asked by Noelle Christine Dilts (Female) from Stifel, Nicolaus & Company, Incorporated on the FQ3 2018 earnings conference call of Myr Group Inc. held on 11/01/2018. Okay. And then in terms of your commentary on renewable energy and some of those projects seeing support. How are you thinking about the -- kind of the knock on the factor, what that does to transmission project demand? I mean, do you see that as driving some of the larger kind of highway projects that would move renewable energy from point A to point B? Or are you thinking about that as driving kind of more of the small to medium-sized intertie type of work? Just curious kind of how you're thinking about that.
Example 4: The question was asked by Angie Storozynski (Female) from Macquarie Research on the FQ1 2019 earnings conference call of Entergy Corporation held on 05/01/2019. I'm sorry. I was just wondering about your regulated renewable power CapEx. You mentioned that some of your jurisdictions might consider more renewable spending going forward once renewables become more economic, but given that there is some sort of some of the tax subsidies, would you -- wouldn't you consider actually potentially accelerating this CapEx?
Example 5: The question was asked by Theresa Chen (Female) from Barclays Bank PLC. On the FQ3 2020 earnings conference call of Valero Energy Corporation held on 10/22/2020. I guess a follow-up question on the renewable diesel front. Clearly, the energy transition is a big theme along with ESG investing and happy to see the additional disclosures consistent with the SASB framework. Can you talk about how you view your renewable diesel position as far as the defensibility of your projected returns? How many of these projects that have been recently announced are you factoring in as ones that could come to fruition? And also on the LCFS prices as well, do you see any risk there?

Panel B: Social-related questions

Example 1: The question was asked by Kelly A. Flynn (Female) from Credit Suisse AG on the FQ4 2012 earnings conference call of Robert Half International Inc. held on 01/29/2013. Okay, great. So I still one -- a last one on the health care, ObamaCare issue. What portion of the temporary employees do you currently pay benefits to?
Example 2: The question was asked by Irene Oiyin Haas (Female) from Wunderlich Securities Inc. on the FQ4 2014 earnings conference call of PDC Energy, Inc. held on 02/19/2015. Okay. In terms of community relations, how are things shaping out these days?
Example 3: The question was asked by Jeffrey Ted Kessler (Male) from Imperial Capital, LLC on the FQ4 2018 earnings conference call of ShotSpotter, Inc. held on 02/19/2019. I recently was at a safe city, secure city's conference. And one of the things that they talked about in terms of funding various programs was a catalyst, something to kind of tie the various services together, around which the public/private partnerships could actually agree on funding. And my question to you is, do you think that you -- in your relationships with companies like Verizon, are you able to get that mind share in which these -- well, let's just say these groups will be able to get mind share around you, too? Taking on, essentially, you being the brand name that they use to go out to the community and try to get funds for, not just ShotSpotter but you serving as a catalyst for other types of safety and public safety measures. In other words, that builds up your value proposition as well.
Example 4: The question was asked by Laurie Katherine Havener Hunsicker (Female) from Stifel, Nicolaus & Company on the FQ1 2011 earnings conference call of Washington Trust Bancorp, Inc. held on 04/25/2011. Okay. And then we're still going to see the charitable foundation this year? Charitable foundation contribution, is that likely?
Example 5: The question was asked by Richard Tobie Safran (Male) from The Buckingham Research Group Incorporated on the FQ1 2012 earnings conference call of Lockheed Martin Corporation held on 04/26/2012. Yes, thanks, Bruce. Bob, at the risk of this being a somewhat sensitive topic, I want to know if I can get a comment from you on negotiations with the Machinists Union of Fort Worth. I want to know if you could talk about the impact of a protracted disagreement. Is this a situation that's serious enough where, for example, you think you have the potential to lay off personnel? And I'm only asking this because the news reports I'm looking at seem to indicate that the Union is making statements like they're ready for a long strike, that kind of thing.

Table IA7
Robustness checks: Using alternative ESG data

This table conducts robustness checks on our main findings in Table 3 Panel A using three alternative ESG data sets. Columns (1)-(3) present the results using the E&S scores from Thomson Reuters' ASSET4 over the period 2005–2018 when it was replaced by Refinitiv's ESG database used in our main analysis. Columns (4)-(6) present the results using the E&S scores from MSCI's KLD Stats over the period 2005–2018 when it was discontinued thereafter. Columns (7)-(9) present the results using the E&S scores from Morningstar's Sustainalytics over the period 2009–2018 when the legacy Sustainalytics database, which measures ESG preparedness and performance, was discontinued in 2019. Other control variables are the same as those in Table 3 and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	ASSET4			KLD			Sustainalytics		
	E&S score	E score	S score	E&S score	E score	S score	E&S score	E score	S score
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
N_female	0.008***	0.010***	0.006**	0.004***	0.003**	0.004***	0.006***	0.007***	0.005***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry × Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.456	0.392	0.407	0.192	0.150	0.173	0.294	0.322	0.247
No. of observations	14,449	14,449	14,449	23,772	23,772	23,772	8,618	8,618	8,618

Table IA8
Robustness checks

This table conducts robustness checks on our main findings in Table 3 Panel A. Panel A includes firm and year fixed effects (instead of industry × year fixed effects). Panel B examines the relation between firms' female analyst ratio and firms' E&S performance. *Female analyst ratio* is the ratio of the number of female analysts to the total number of analysts covering a firm in a given year. Panel C examines the relation between having female analyst coverage and firms' E&S performance. *Having female analyst* is an indicator variable that takes the value of one if there is at least one female analyst who covers a firm in a given year, and zero otherwise. Panel D examines the non-linear effects of female analyst coverage by employing a set of indicator variables capturing the number of female analysts covering a firm. *N_female = 1* is an indicator variable that takes the value of one if there is one female analyst who covers a firm in a given year. *N_female = 2*, *N_female = 3*, and *N_female = 4* are defined analogously. Panel E examines the relation between female analyst coverage and firms' E&S performance separating by their brokerage size. *N_female_Top10* is the number of female analysts, from one of the top 10 brokers, who cover a firm in a given year. We determine whether a broker is one of the top 10 brokers based on its size. *N_female_non-Top10* is the number of female analysts, not from one of the top 10 brokers, who cover a firm in a given year. Panel F conducts robustness checks on our main findings in Table 3 Panel A by controlling for gender differences in analyst general (firm) experience. *Female relative general experience* is the ratio of the average general experience of female analysts covering a firm to that of male analysts covering the same firm in a given year. *Female relative firm experience* is defined analogously. Panel G conducts robustness checks on our main findings in Table 3 Panel A by controlling for SRI fund ownership. *SRI fund ownership* is the faction of shares outstanding held by socially responsible investment (SRI) funds. The SRI fund ownership data is from Heath et al. (2023). The sample consists of 15,040 firm-year observations (representing 3,147 firms) with data on SRI fund ownership over the period 2010–2020. Other control variables are the same as those in Table 3 and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Including firm and year fixed effects

Variable	E&S score (1)	E score (2)	S score (3)
N_female	0.004**	0.005**	0.003
	(0.002)	(0.002)	(0.002)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R^2	0.833	0.806	0.793
No. of observations	20,423	20,423	20,423

Panel B: Female analyst ratio and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
Female analyst ratio	0.038**	0.049***	0.027*
	(0.016)	(0.018)	(0.016)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.522	0.514
No. of observations	20,423	20,423	20,423

Panel C: Having female analyst coverage and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
Having female analyst	0.015***	0.021***	0.010*
	(0.005)	(0.006)	(0.006)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.522	0.514
No. of observations	20,423	20,423	20,423

Panel D: The non-linear effect of female analyst coverage and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
N_female = 1	0.008	0.012**	0.003
	(0.005)	(0.006)	(0.006)
N_female = 2	0.032***	0.039***	0.025***
	(0.009)	(0.010)	(0.009)
N_female = 3	0.046***	0.062***	0.030**
	(0.014)	(0.015)	(0.014)
N_female = 4	0.045**	0.051**	0.039*
	(0.023)	(0.025)	(0.023)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.522	0.514
No. of observations	20,423	20,423	20,423

Panel E: Separating female analysts by their brokerage size

Variable	E&S score (1)	E score (2)	S score (3)
N_female_Top10	0.019***	0.022***	0.015***
	(0.005)	(0.006)	(0.006)
N_female_non-Top10	0.011**	0.014***	0.008*
	(0.005)	(0.005)	(0.005)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.523	0.514
No. of observations	20,423	20,423	20,423

Panel F: Controlling for gender differences in experience

Variable	E&S score (1)	E score (2)	S score (3)
N_female	0.013***	0.016***	0.009**
	(0.004)	(0.004)	(0.004)
Female relative general experience	-0.001	-0.002	0.000
	(0.004)	(0.004)	(0.004)

Female relative firm experience	0.010*	0.012**	0.008
	(0.005)	(0.006)	(0.006)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.523	0.514
No. of observations	20,423	20,423	20,423

Panel G: Controlling for SRI fund ownership

Variable	E&S score (1)	E score (2)	S score (3)
N_female	0.016***	0.018***	0.013***
	(0.004)	(0.005)	(0.004)
SRI fund ownership	1.581***	1.545***	1.615***
	(0.499)	(0.559)	(0.529)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.584	0.545	0.543
No. of observations	15,040	15,040	15,040

Table IA9
Female analysts and corporate E&S performance: Change-on-change regressions

This table examines the dynamic effect of female analyst coverage on firms' E&S performance using change-on-change regressions. Panel A presents the sample distribution of four types of changes in female analyst coverage from year *t-2* and *t-1*. Panel B examines the change from having no female analyst to having female analysts on future changes of firms' E&S performance (group 2) relative to a subsample of firms with no female analyst coverage and experiencing no change in coverage (group 1). Panel C examines the change from having female analysts to having no female analyst on future changes of firms' E&S performance (group 3) relative to a subsample of firms with female analyst coverage and experiencing no change in coverage (group 4). The dependent variables are changes in firms' E&S performance from year *t-1* to year *t* (D0), year *t* to year *t+1* (D1), from year *t* to year *t+2* (D2), from year *t* to year *t+3* (D3). Key explanatory variables are lagged one-year changes from year *t-2* to year *t-1* (LD1). Other control variables are the same as those in Table 3, measured as changes from year *t-2* to *t-1,* and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Sample distribution of four types of changes in female analyst coverage

Subsamples	N
Group 1: LD1_Female analyst indicator stays 0	4,484
Group 2: LD1_Female analyst indicator switch from 0 to 1	1,022
Group 3: LD1_Female analyst indicator switch from 1 to 0	1,047
Group 4: LD1_Female analyst indicator stays 1	2,361

Panel B: Dynamic effects of gaining female analyst coverage relative to having no female analyst coverage on E&S scores

	E&S score			
	D0	D1	D2	D3
Variable	(1)	(2)	(3)	(4)
LD1_Female analyst indicator switch from 0 to 1	0.003	0.009**	0.010*	0.014**
	(0.003)	(0.004)	(0.005)	(0.007)
LD1_Analyst coverage	-0.004	-0.000	-0.000	0.003
	(0.003)	(0.003)	(0.004)	(0.005)
Other controls	YES	YES	YES	YES
Constant	YES	YES	YES	YES
Industry × Year FE	YES	YES	YES	YES
Adjusted R^2	0.098	0.078	0.091	0.101
No. of observations	5,506	5,506	5,506	5,506

Panel C: Dynamic effects of losing female analyst coverage relative to having female analyst coverage on E&S scores

	E&S score			
	D0	D1	D2	D3
Variable	(1)	(2)	(3)	(4)
LD1_Female analyst indicator switch from 1 to 0	0.004	-0.005	-0.012**	-0.011*
	(0.004)	(0.004)	(0.005)	(0.007)
LD1_ Analyst coverage	-0.002	0.007*	0.008	0.003
	0.004	-0.005	-0.012**	-0.011*
Other controls	YES	YES	YES	YES
Constant	YES	YES	YES	YES

Industry × Year FE	YES	YES	YES	YES
Adjusted R^2	0.099	0.107	0.107	0.124
No. of observations	3,408	3,408	3,408	3,408

Table IA10
List of broker closures over time

This table lists the 24 broker closure events over the period 2005–2017 used in our identification test in Table 4, the number of the treated firms previously covered by a female analyst from an exited broker, and the number of industries covered by the broker at the time of closure.

Closure date	Broker	# treated firms	# Fama-French 48-industry covered
Mar. 2005	JB Hanauer Co.	2	1
May 2005	Tradition Asiel Securities	2	1
June 2005	Independent Research Group, LLC	2	2
Aug. 2005	Wells Fargo Securities	3	3
May 2006	Variant Research Corp	2	1
Aug. 2006	Foresight Research Solution	3	1
Sept. 2006	Moors & Cabot Capital	5	2
June 2007	Prudential Equity Group	16	6
Oct. 2007	Cathay Financial	2	2
Feb. 2009	Stanford Group Company	2	2
Dec. 2009	Ragen Mackenzie	5	3
Feb. 2010	FTN Equity Capital Markets	12	3
Feb. 2010	Pali Research	12	4
June 2010	Jesup & Lamont Securities	5	2
Feb. 2012	Kaufman Bros	9	3
Mar. 2012	Collins Stewart	23	7
June 2012	Auriga USA	7	5
June 2013	BGB Securities, Inc., Research Division	1	1
Oct. 2014	ISI Group Inc., Research Division	12	4
Dec. 2014	Miller Tabak + Co., LLC, Research Division	4	2
June 2016	Topeka Capital Markets Inc., Research Division	7	3
July 2016	Portales Partners, LLC	7	1
July 2016	BB&T Capital Markets, Research Division	23	7
Mar. 2017	Avondale Partners, LLC, Research Division	11	7
Total		177	

Table IA11
E&S discussions and corporate E&S performance

This table examines the relation between analysts' E&S-related discussions in analyst reports and during earnings conference calls and firms' E&S performance. *Ln(1 + N_E&S sentences)* is the natural logarithm of one plus the average number of E&S-related sentences in reports by analysts covering a firm in a given year. *Ln(1 + N_E sentences)* and *Ln(1 + N_S sentences)* are defined analogously. *Ln(1 + N_E&S questions)* is the natural logarithm of one plus the average number of E&S-related questions raised by analysts on a firm's calls in a given year. *Ln(1 + N_E questions)* and *Ln(1 + N_S questions)* are defined analogously. Other control variables are the same as those in Table 3 and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Variable	E&S score (1)	E&S score (2)	E&S score (3)	E&S score (4)	E&S score (5)	E&S score (6)
N_female	0.009**	0.011**	0.010**	0.010**	0.012***	0.012***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ln(1 + N_E&S sentences)	0.036***					
	(0.008)					
N_female × Ln(1 + N_E&S sentences)	0.016**					
	(0.007)					
Ln(1 + N_E sentences)		0.045***				
		(0.010)				
N_female × Ln(1 + N_E sentences)		0.015*				
		(0.008)				
Ln(1 + N_S sentences)			0.028*			
			(0.017)			
N_female × Ln(1 + N_S sentences)			0.026*			
			(0.014)			
Ln(1 + N_E&S questions)				0.047**		
				(0.024)		
N_female × Ln(1 + N_E&S questions)				0.044*		
				(0.026)		
Ln(1 + N_E questions)					0.117**	
					(0.058)	
N_female × Ln(1 + N_S questions)					0.115**	
					(0.056)	
Ln(1 + N_S questions)						0.040
						(0.028)
N_female × Ln(1 + N_S questions)						0.031
						(0.030)
Other controls	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES
Industry × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.562	0.562	0.559	0.559	0.559	0.559
No. of observations	20,423	20,423	20,423	20,423	20,423	20,423

Table IA12
Structure topic model results

This table presents the top words and assigned labels for each topic identified by the Structural Topic Modeling (STM) analysis. The top words are determined using the score criteria, which divides the log frequency of a word in a topic by its log frequency in other topics. Labels are assigned based on the collections of words most strongly associated with each topic. The last column indicates whether the topic is more prevalent among male analysts, female analysts, or has similar prevalence for both genders. Detailed descriptions of the STM methodology and estimation procedure are provided in our technical appendix in the Internet Appendix.

Corpus	Topic	Top words	Label	Emphasis by gender
Environmental issues – analyst reports	1	activist, market, gas, products, energy, cash, projects, results	Market Dynamics & Energy Sector	Male
	2	overview, growth, power, cost, share, margins, industrial, segments	Growth & Industrial Performance	Similar prevalence
	3	company, prices, impact, customers, capital, product, planning, term	Strategic Planning & Stakeholders	Female
	4	sales, demand, industry, increase, report, environment, regulations, financial	Sales & Environmental Factors	Similar prevalence
Social issues – analyst reports	1	finra/sipc, credit, report, company, growth, regulatory, liability, clients	Regulatory Compliance	Female
	2	member, investment, plan, expected, cash, healthcare, issues, act	Management & Investment Strategies	Male
	3	auditor, market, revenue, costs, stock, risks, future, shares	Market Dynamics & Operational Performance	Male
	4	employees, price, products, risk, earnings, business, safety, customers	Employees & Risk Management	Female
Environmental issues – earnings calls	1	energy, business, growth, executive, industry, renewable, flow, impact	Energy Sector & Business Growth	Male
	2	guess, cost, gas, prices, environment, sales, capex, electric	Cost Management & Environmental Factors	Female
	3	look, quarter, oil, projects, pricing, market, opportunities, earnings	Market Opportunities & Capital Projects	Female
	4	amortization, demand, mix, infrastructure, customers, spending, future, company	Financial Performance & Operational Updates	Similar prevalence
Social issues – earnings calls	1	officer, market, opportunity, competitive, patients, strategy, margins, competitors	Leadership & Stakeholders	Female
	2	quarter, million, expense, president, cash, savings, bonus, stock	Financial Metrics & Cost Management	Male
	3	amortization, hiring, growth, plans, products, loyalty, employees, productivity	Operational Changes & Human Resources	Male
	4	sales, business, customer, markets, product, environment, brand, clients	Sales & Brand Impacts	Female

Table IA13
Female analyst experience and reputation and corporate E&S performance

This table examines the relations between female analyst experience and reputation and firms' E&S performance. Panel A presents the relation between female analyst general experience and firms' E&S performance. At a point in time, general experience refers to the number of years since an analyst first appears in the I/B/E/S Detail History file following Bradley, Gokkaya, and Liu (2017). *Female more general experience* is an indicator variable that takes the value of one if at least one of a firm's female analysts has general experience above the median of general experience of the other analysts (excluding the focal analyst) covering the same firm in a given year, and zero otherwise. Panel B presents the relation between female analyst firm-specific experience and firms' E&S performance. At a point in time, firm-specific experience refers to the number of years since an analyst first starts covering a firm in the I/B/E/S Detail History file following Bradley, Gokkaya, and Liu (2017). *Female more firm experience* is an indicator variable that takes the value of one if at least one of a firm's female analysts has firm-specific experience above the median of firm-specific experience of the other analysts (excluding the focal analyst) covering the same firm in a given year, and zero otherwise. Panel C presents the relation between having a female star analyst and firms' E&S performance. *Female star analyst* is an indicator variable that takes the value of one if at least one of a firm's female analysts has the All-Star status in a given year, and zero otherwise. Other control variables are the same as those in Table 3 and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Female analyst general experience and corporate E&S performance.

Variable	E&S score (1)	E score (2)	S score (3)
N_female	-0.002	-0.000	-0.003
	(0.006)	(0.007)	(0.006)
Female more general experience	0.010	0.011	0.009
	(0.007)	(0.008)	(0.008)
N_female × Female more general experience	0.018***	0.021**	0.015**
	(0.007)	(0.008)	(0.007)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.561	0.524	0.515
No. of observations	20,423	20,423	20,423

Panel B: Female analyst firm-specific experience and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
N_female	-0.003	-0.002	-0.004
	(0.005)	(0.006)	(0.005)
Female more firm experience	0.025***	0.024***	0.026***
	(0.008)	(0.009)	(0.008)
N_female × Female more firm experience	0.020***	0.023***	0.016**
	(0.007)	(0.008)	(0.007)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.562	0.525	0.517
No. of observations	20,423	20,423	20,423

Panel C: Female star analysts and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
N_female	0.010***	0.013***	0.007*
	(0.004)	(0.004)	(0.004)
Female star analyst	0.049***	0.045**	0.054***
	(0.017)	(0.019)	(0.016)
N_female × Female star analyst	0.003	0.005	0.001
	(0.009)	(0.010)	(0.009)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.561	0.524	0.516
No. of observations	20,423	20,423	20,423

Table IA14
Female analysts, female directors, and female executives and corporate E&S performance

This table examines the relations between female analysts, female directors, and female executives and firms' E&S performance. Panel A presents the relations between female analysts, female directors, and firms' E&S performance. *N_female directors* is the number of female directors on a firm's board in a given year. Panel B presents the relations between female analysts, female executives, and firms' E&S performance. *N_female executives* is the number of female executives of a firm in a given year. Other control variables are the same as those in Table 3 and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Female analysts, female directors, and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
N_female	0.010*	0.008	0.011**
	(0.005)	(0.006)	(0.005)
N_female directors	0.042***	0.039***	0.044***
	(0.003)	(0.003)	(0.003)
N_female × N_female directors	-0.000	0.002	-0.002
	(0.002)	(0.002)	(0.002)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.582	0.541	0.538
No. of observations	20,423	20,423	20,423

Panel B: Female analysts, female executives, and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
N_female	0.011**	0.012**	0.009*
	(0.005)	(0.005)	(0.005)
N_female executives	0.017***	0.012*	0.022***
	(0.005)	(0.006)	(0.005)
N_female × N_female executives	0.002	0.004	-0.000
	(0.004)	(0.005)	(0.004)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.536	0.510	0.472
No. of observations	20,423	20,423	20,423

Table IA15
Female analysts' E&S-related discussions/questions and career outcomes

This table examines the relation between female analysts' E&S-related discussions/questions and their career outcomes (*Star analyst* and *Forecast accuracy*). *Star analyst* is an indicator variable that takes the value of one if an analyst is accredited to All-Star status, and zero otherwise. *Forecast accuracy* is the negative value of the average of the absolute forecast error made by an analyst in a given year, demeaned by the average absolute forecast error of all analysts covering the same firm in the same year (Clement 1999). The absolute forecast error is the absolute value of the difference between an analyst's annual EPS forecast and the actual EPS, using the I/B/E/S Unadjusted Detail file. Panel A presents the relations between female analysts' E&S-related discussions in analyst reports and their career outcomes. At the analyst-firm-year level, *Ln(1 + N_E&S sentences)* is the natural logarithm of one plus the average number of E&S-related sentences among the reports written by an analyst covering a firm in a given year. *Ln(1 + N_E sentences)* and *Ln(1 + N_S sentences)* are defined analogously. The sample period is from 2004 to 2020 due to data availability. Panel B presents the relations between female analysts' E&S-related questions during earnings conference calls and their career outcomes. At the analyst-firm-year level, *Ln(1 + N_E&S questions)* is the natural logarithm of one plus the average number of E&S-related questions raised by an analyst during a firm's calls in a given year. *Ln(1 + N_E questions)* and *Ln(1 + N_S questions)* are defined analogously. The sample period is from 2007 to 2020 due to data availability. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the analyst times year level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Analyst-firm-year-level regressions examining the relation between E&S-related discussions in reports and analyst career outcomes

	Star analyst			Forecast accuracy		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.004	-0.005	-0.007	0.886	-0.062	3.305
	(0.008)	(0.007)	(0.007)	(3.375)	(3.032)	(3.109)
Ln(1 + N_E&S sentences)	-0.001			-3.806**		
	(0.002)			(1.938)		
Female × Ln(1 + N_E&S sentences)	-0.005			2.286		
	(0.007)			(4.523)		
Ln(1 + N_E sentences)		0.001			-4.232*	
		(0.003)			(2.293)	
Female × Ln(1 + N_E sentences)		-0.005			5.954	
		(0.008)			(4.862)	
Ln(1 + N_S sentences)			-0.004			-1.333
			(0.003)			(2.910)
Female × Ln(1 + N_S sentences)			0.005			-7.496
			(0.011)			(8.103)
Education	0.009***	0.009***	0.009***	0.117	0.138	0.069
	(0.003)	(0.003)	(0.003)	(1.059)	(1.059)	(1.059)
CFA	0.013***	0.013***	0.013***	4.277**	4.314**	4.208**
	(0.005)	(0.005)	(0.005)	(1.706)	(1.705)	(1.704)
Forecast frequency	0.007***	0.007***	0.007***	0.907***	0.933***	0.956***
	(0.001)	(0.001)	(0.001)	(0.336)	(0.335)	(0.335)
Forecast horizon	0.000	0.000	0.000	0.012	0.012	0.011
	(0.000)	(0.000)	(0.000)	(0.010)	(0.010)	(0.010)
# firms followed	0.003***	0.003***	0.003***	-0.122	-0.123	-0.115
	(0.000)	(0.000)	(0.000)	(0.138)	(0.138)	(0.138)
# industries followed	0.003**	0.003**	0.003**	0.083	0.085	0.069
	(0.001)	(0.001)	(0.001)	(0.565)	(0.565)	(0.565)
General experience	0.006***	0.006***	0.006***	0.101	0.104	0.098
	(0.001)	(0.001)	(0.001)	(0.188)	(0.188)	(0.188)

Constant	YES	YES	YES	YES	YES	YES
Firm × Year FE	YES	YES	YES	YES	YES	YES
Broker × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.346	0.346	0.346	0.098	0.098	0.098
No. of observations	126,029	126,029	126,029	99,871	99,871	99,871

Panel B: Analyst-firm-year-level regressions examining the relation between E&S-related questions during calls and analyst career outcomes

	Star analyst			Forecast accuracy		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.022***	-0.021***	-0.020***	2.246	2.119	1.986
	(0.007)	(0.007)	(0.007)	(3.110)	(2.773)	(3.034)
Ln(1 + N_E&S questions)	0.006**			3.758*		
	(0.003)			(2.205)		
Female × Ln(1 + N_E&S questions)	0.012			-1.982		
	(0.008)			(5.543)		
Ln(1 + N_E questions)		0.013***			5.527	
		(0.004)			(4.027)	
Female × Ln(1 + N_S questions)		0.035*			-5.940	
		(0.020)			(11.036)	
Ln(1 + N_S questions)			0.005*			2.956
			(0.003)			(2.509)
Female × Ln(1 + N_S questions)			0.004			-1.175
			(0.008)			(6.186)
Education	0.008***	0.008***	0.008***	-0.651	-0.651	-0.638
	(0.003)	(0.003)	(0.003)	(1.149)	(1.150)	(1.149)
CFA	0.004	0.004	0.004	2.655	2.669	2.664
	(0.005)	(0.005)	(0.005)	(1.835)	(1.836)	(1.836)
Forecast frequency	0.007***	0.007***	0.007***	0.820**	0.840**	0.836**
	(0.001)	(0.001)	(0.001)	(0.392)	(0.392)	(0.392)
Forecast horizon	0.000	0.000	0.000	0.012	0.012	0.012
	(0.000)	(0.000)	(0.000)	(0.011)	(0.011)	(0.011)
# firms followed	0.005***	0.005***	0.005***	-0.202	-0.202	-0.201
	(0.000)	(0.000)	(0.000)	(0.156)	(0.156)	(0.156)
# industries followed	-0.002*	-0.002*	-0.002*	-0.388	-0.395	-0.391
	(0.001)	(0.001)	(0.001)	(0.605)	(0.604)	(0.604)
General experience	0.006***	0.006***	0.006***	0.282	0.291	0.286
	(0.001)	(0.001)	(0.001)	(0.189)	(0.189)	(0.189)
Constant	YES	YES	YES	YES	YES	YES
Firm × Year FE	YES	YES	YES	YES	YES	YES
Broker × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.446	0.446	0.446	0.080	0.080	0.080
No. of observations	91,855	91,855	91,855	78,448	78,448	78,448

Table IA16
Sub-period analysis: The Paris Agreement

This table examines whether there is any temporal variation in the strength of the positive association between female analyst coverage and corporate E&S performance. We divide the sample period 2005–2021 into two sub-periods: 2005–2015 and 2016–2021 and employ the same regression specification as that in Table 3. Other control variables are the same as those in Table 3 and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Female analysts and corporate E&S performance over the period 2005–2015

	E&S score	E score	S score
Variable	(1)	(2)	(3)
N_female	0.013***	0.016***	0.011**
	(0.005)	(0.006)	(0.005)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.491	0.463	0.442
No. of observations	8,831	8,831	8,831

Panel B: Female analysts and corporate E&S performance over the period 2016–2021

	E&S score	E score	S score
Variable	(1)	(2)	(3)
N_female	0.011**	0.014***	0.008*
	(0.004)	(0.005)	(0.005)
Other controls	YES	YES	YES
Constant	YES	YES	YES
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.609	0.573	0.560
No. of observations	11,592	11,592	11,592