Female Equity Analysts and Corporate Environmental and Social Performance[*]

Kai Li, Feng Mai, Gabriel Wong, Chelsea Yang, and Tengfei Zhang

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Abstract

Using a sample of over 10,000 sell-side equity analysts from 2005−2021, we show that there is a positive and significant association between a firm's female analyst following and its environmental and social (E&S) performance. We further show that after an exogenous drop in female analyst coverage due to broker closures, firms experience a 7% decrease in their E&S scores. Finally, we develop machine learning models to sift through 2.4 million analyst reports and over 120,000 earnings call transcripts and show that female equity analysts are more likely to discuss E&S issues in reports and during calls than their male counterparts.

Keywords: female equity analysts; analyst monitoring; corporate environmental and social performance; natural language processing; data-centric AI; FinBERT; analyst reports; earnings conference calls

JEL classification: G24; G30; G40

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[*] Kai Li: Sauder School of Business, University of British Columbia. Email: kai.li@sauder.ubc.ca. Feng Mai: School of Business, Stevens Institute of Technology. Email: feng.mai@stevens.edu. Gabriel Wong: Department of Economics, Cardiff University. Email: wonggk@cardiff.ac.uk. Chelsea Yang: Sauder School of Business, University of British Columbia. Email: chunxue.yang@sauder.ubc.ca. Tengfei Zhang: Rutgers School of Business-Camden, Rutgers University. Email: tengfei.zhang@rutgers.edu. We are grateful for helpful comments from Ling Cen, Rui Dai, David Du, Nick Gantchev, Jack He (discussant), Allen Huang, Po-Hsuan Hsu, Sterling Huang, Yaling Jin (discussant), Chukwuma Kim, Frank Li, Rachel Peng, Meng Qu, Kate Suslava (discussant), Hongping Tan, Julian Vahl, Ting Xu, Aaron Yoon (discussant), and Yuxiang Zheng, seminar participants at Columbia Financial Economics Colloquium, Fordham University, HEC Montreal, McGill University, Rutgers University, University of Birmingham, and Western University, and conference participants at the Third Canadian Sustainable Finance Network Conference (Victoria), the UF Research Conference on Machine Learning in Finance (virtual), the Conference on CSR, the Economy, and Financial Markets (Chicago), the SFS Cavalcade Asia-Pacific Conference (virtual), and the Weinberg Center/ECGI Corporate Governance Symposium (Newark). The paper was the recipient of the John L. Weinberg/IRRCi Best Paper Award. We acknowledge financial support from the Social Sciences and Humanities Research Council of Canada (Grant Number: 435-2022-0285) and the Sauder Exploratory Research Grants Program. Li acknowledges financial support from the Canada Research Chair in Corporate Governance. Zhang acknowledges data support from the Whitcomb Center for Research in Financial Services at Rutgers University. All errors are our own.

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Abstract

Using a sample of over 10,000 sell-side equity analysts from 2005–2021, we show that there is a positive and significant association between a firm's female analyst following and its environmental and social (E&S) performance. We further show that after an exogenous drop in female analyst coverage due to broker closures, firms experience a 7% decrease in their E&S scores. Finally, we develop machine learning models to sift through 2.4 million analyst reports and over 120,000 earnings call transcripts and show that female equity analysts are more likely to discuss E&S issues in reports and during calls than their male counterparts.

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"*Since then, PEP has continuously taken steps to lessen its environmental impact from rolling out its first all-electric delivery trucks in 2010 to establishing its first compressed natural gas fueling station in 2013. Currently, PEP aims to source 100% of its direct farmer sourced agricultural inputs from sustainable farming in 2020 (vs. 51% in 2018).*"

- Vivien Azer

Managing director and senior research analyst at Cowen and Company on PepsiCo, March 3, 2020.

1. Introduction

Sell-side equity analysts are known for their information discovery and interpretation roles, with implications for corporate investment and financing policies (Derrien and Kecskés 2013; He and Tian 2013; Huang, Lehavy, Zang, and Zheng 2018; Birru, Gokkaya, Liu, and Stulz 2022).[1] Equity analysts also help mitigate agency problems and improve corporate governance and decision-making (see, for example, Yu 2008; Chen, Harford, and Lin 2015). In this paper, we fill a void in the literature by examining the role of female equity analysts in corporate environmental and social (E&S) performance.

We focus on female equity analysts because of well-documented gender differences in values and willingness to delay gratification that have implications for female analysts monitoring corporate E&S performance. Surveys in both psychology and economics (Beutel and Marini 1995; Schwartz and Rubel 2005; Bertrand 2011) indicate that women, relative to men, tend to score higher on values related to community and compassion and score lower on materialism, and that relative to men, women have more prosocial and altruistic responses to, and preferences for, redistribution and equity. Relatedly, experimental and survey evidence in psychology (Silverman 2003; Castillo, Ferraro, Jordan, and Petrie 2011) shows that women,

[1] Prior literature documents two main channels through which analysts help enhance firms' information environments (see, for example, Bradshaw, Ertimur, and O'Brien 2018; Huang, Lehavy, Zang, and Zheng 2018). First, analysts engage in information discovery, generating new information by tracking financial statements and attending conference calls, including those of a firm's competitors, suppliers, and the like. Second, analysts engage in information interpretation, by quantifying the value implications of corporate events, such as earnings releases or other industry and macro news.

on average, are more patient and less impulsive than men when trading off present versus future values. These gender differences in values and willingness to delay gratification suggest that compared to male equity analysts, female equity analysts will be more likely to care and express their concerns about a firm's E&S performance. Given analysts' information discovery and interpretation roles in capital markets, firms followed by female analysts will pay more attention and invest more in E&S policies and practices than their counterparts not followed by female analysts. Our main hypothesis is thus as follows: There is a positive association between a firm's female equity analyst following and its E&S performance.

Using a novel sample of over 10,000 sell-side equity analysts with gender data and the Refinitiv Environmental, Social, and Governance (ESG) database 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. In terms of economic significance, adding one more female analyst following a firm is associated with a 3.3% increase in that firm's E&S score relative to the sample mean. This finding is robust to alternative measures of corporate E&S performance from different ESG rating providers and real E&S outcomes, such as carbon emissions and workplace safety misconduct cases.

Employing broker closures as a quasi-natural experiment and the difference-in-differences (DID) approach, we show that a drop in female equity analyst coverage due to broker closures leads to a significant decrease in firms' E&S scores, suggesting that there is a causal effect of female analyst coverage on firm-level E&S performance. In terms of economic significance, losing one female equity analyst following a firm due to broker closures leads to a 7.3% drop in that firm's E&S score.

To uncover the underlying economic mechanisms, we further hypothesize that female equity analysts are more likely to discuss E&S issues in their analyst reports and/or to raise questions regarding E&S issues during earnings conference calls than their male counterparts.

To test this hypothesis, we utilize over 2.4 million analyst reports and over 120,000 earnings call transcripts. Because E&S-related discussions encompass a broad range of topics and linguistic expressions, conventional keyword-based textual analysis methods are often inadequate. Modern machine learning methods, which rely on high-quality domain-specific training examples, offer an effective alternative. Yet annotating these examples can potentially be a costly endeavor.

Drawing on the recent advancements in data-centric AI that prioritize data collection and quality over model design (Whang et al. 2023; Zha et al. 2023), we develop a new active learning approach to efficiently search for and annotate E&S-related discussions from large corpora of analyst reports and earnings call transcripts.[2] Utilizing the curated training data, we 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 questions (during earnings calls) about E&S issues.

Consistent with our hypothesis, we show that female analysts' reports contain more discussions about E&S issues than male analysts' reports. Similarly, we show that female analysts are more likely to raise E&S-related questions during conference calls than male analysts. Moreover, we establish that there are positive associations between analysts having E&S-related discussions in reports and/or asking E&S-related questions during calls and corporate E&S performance. Importantly, such positive association is strengthened by the number of female analysts following a firm.

Finally, in terms of cross-sectional variations in the positive association between female analyst coverage and corporate E&S performance, we show that this positive

[2] In a nutshell, active learning uses a preliminary model to help select domain-specific training examples that are likely to be most useful for improving the model. In the process, we iteratively label training examples and refine the model. As a result, active learning, which uses a smaller yet high-quality training data set, is more cost-effective than other fine-tune algorithms. See Section 3 and our technical appendix for details.

association is significant only when there is more than one female analyst following. Moreover, this positive association is stronger in firms followed by female analysts with more general and/or firm-specific experience, whereas this positive association is invariant to the presence of female directors/executives.

We conclude that female equity analysts play a significant monitoring role in enhancing corporate E&S performance.

Our paper makes three contributions to the literature. First and foremost, we contribute to the literature on gender and finance. Prior work shows that gender differences in preferences and values have implications for corporate investment decisions, financing policies, workplace practices, and corporate social responsibility (CSR) (see, for example, Huang and Kisgen 2013; Matsa and Miller 2013; Levi, Li, and Zhang 2014; Tate and Yang 2015; Hsu, Li, and Pan 2023). Yu (2008), Irani and Oesch (2013), Chen, Harford, and Lin (2015), Guo, Pérez-Castrillo, and Toldrà-Simats (2019), and Bradley, Mao, and Zhang (2022) establish evidence of equity analysts as monitors who help mitigate agency problems and improve corporate decision-making. Bridging these two streams of the literature, we show that it is female equity analyst coverage of a firm that is behind its improved E&S performance.

Second, we contribute to the literature that employs computational methods to study large, unstructured data in finance and accounting – as exemplified by recent work in measuring corporate environmental exposure (Kölbel, Leippold, Rillaerts, and Wang 2022; Li, Shan, Tang, and Yao 2022; Sautner, Vilkov, van Lent, and Zhang 2023). Several recent studies have adopted pre-trained large language models like BERT for text classification (Kölbel et al. 2022; Huang, Wang, and Yang 2023). Our work differs from extant literature by incorporating the principles of data centric-AI, which emphasize that high-quality training data set is just as critical as new modeling techniques. In this respect, we present a novel active learning approach to identify domain-specific training examples from substantially larger and more diverse data sets than previously explored.[3] Our approach, when combined with a pre-trained large language model such as FinBERT (Huang, Wang, and Yang 2023), proves to be an effective strategy in accurately classifying text, particularly in situations when there is limited training data due to specialized language and terminology in diverse contexts. We show that domain-specific training examples can significantly improve model performance. Moreover, a model interpretability analysis of our trained models reveals that E&S discussions in analyst reports and earnings call transcripts have distinct focuses. These insights underscore the importance of curating high-quality training examples across various corpora and the necessity of adopting a data-centric perspective in analyzing financial texts.

Third and finally, we contribute to the growing literature on CSR. Complementary to the strand of the literature that focuses on firm and managerial characteristics to explain firms' CSR investments (see, for example, Cronqvist and Yu 2017; Davidson, Dey, and Smith 2019; Dyck, Lins, Roth, and Wagner 2019; Shive and Foster 2020; Starks, Venkat, and Zhu 2020; Dyck, Lins, Roth, Towner, and Wagner 2023), our findings highlight the significant monitoring role female equity analysts play in enhancing corporate E&S performance. We leverage the largest sample of analyst reports in the literature to delineate female analysts' channels of influence. In the process, we develop new firm-year level measures of E&S exposure. These measures incorporate the viewpoints of analysts and offer several advantages over existing measures. Notably, they are less susceptible to green-washing and window dressing. Moreover, in contrast to much of the existing literature that focuses on measuring firms' climate exposure, our paper takes the lead in introducing a new text-based measure of firms' exposure to social issues.

[3] We employ over 2.4 million analyst reports and over 120,000 call transcripts, compared to about 50,000 10-K filings in Kölbel et al. (2022), 140,000 earnings calls in Li et al. (2022), and 665,000 analyst reports in Bellstam, Bhagat, and Cookson (2021).

2. Literature Review and Hypothesis Development

2.1. Literature review

Our paper is closely related to the literature on gender and finance. Prior work shows that gender differences in preferences and values have implications for corporate policies. Zooming in on gender differences in overconfidence, Huang and Kisgen (2013) find that firms led by female executives make fewer acquisitions and issue less debt than those led by male executives. Levi, Li, and Zhang (2014) find that firms with female directors are less likely to make acquisitions and when they do so, pay lower bid premia. Both Matsa and Miller (2013) and Tate and Yang (2015) find that female leaders cultivate labor-friendly and/or more gender-equal cultures within their firms. Hsu, Li, and Pan (2023) show a positive association between board gender diversity and corporate environmental performance.

Our paper is also related to the literature on the information intermediary role of equity analysts (see, for example, the review chapter by Bradshaw, Ertimur, and O'Brien 2018). Jensen and Meckling (1976) argue that equity analysts, in addition to their information discovery and interpretation roles, are also monitors who help mitigate agency problems. Yu (2008) finds that firms followed by more analysts manage their earnings less. Irani and Oesch (2013) show that a drop in the number of analysts following a firm leads to a deterioration in that firm's financial reporting quality. Chen, Harford, and Lin (2015) show that as a firm experiences a drop in analyst coverage, shareholders value internal cash holdings less, its CEO receives higher excess compensation, its management is more likely to make value-destroying acquisitions, and its managers are more likely to engage in earnings management activities. Guo, Pérez-Castrillo, and Toldrà-Simats (2019) find that an increase in the number of analysts following a firm leads that firm to cut R&D expenses, acquire more innovative firms, and invest in corporate venture capital, resulting in more future patents and citations as well as the novelty of their innovations. Bradley, Mao, and Zhang (2022) show that firms' work-related injury rates are negatively associated with their levels of analyst coverage.

Moreover, our paper is related to the nascent literature employing computational linguistic methods to capture corporate E&S exposure, risk, and performance. Those extant methods can be broadly classified into three approaches. The first approach relies on manually constructed keyword lists. For example, Henry, Jiang, and Rozario (2021) examine earnings call transcripts of firms in environmentally sensitive industries to generate a list of environment-related keywords. The second approach employs automated keyword discovery methods such as word embeddings or the algorithm proposed by King, Lam, and Roberts (2017). Methods like these start with a list of seed words or phrases, which are then expanded based on word associations in text (see, for example, Amel-Zadeh, Chen, Mussalli, and Weinberg 2022; Briscoe-Tran 2022; Li et al. 2022; Sautner et al. 2023).[4] The advantage of these methods is that they identify domain-specific keywords without requiring extensive human input. The third and relatively new approach is using a machine learning model to classify whether a sentence (or a question) is E&S relevant. This approach is more accurate because the model takes the context of the entire sentence into account when making predictions. In particular, Kölbel et al. (2022) fine-tune a Bidirectional Encoder Representation from Transformers model (BERT, Devlin, Chang, Lee, and Toutanova 2018) to find sentences related to transition risk and physical climate risk in 10-K filings. Huang, Wang, and Yang (2023) fine-tune FinBERT, a BERT model pre-trained on financial text (e.g., annual reports), to label ESG discussions. Both papers demonstrate that BERT-based models are superior to conventional text classification models that rely on bag-of-words or word embeddings.

[4] For example, Li et al. (2022) compile a comprehensive list of climate- and weather-related keywords from multiple sources, including the Federal Emergency Management Agency's (FEMA) disaster announcements, a meteorology textbook, weather.com news, and climate change reports. They then combine their climate dictionary with risk synonyms to identify the share of conversations on climate risk in earnings conference calls.

Finally, our paper is related to the growing literature on determinants of CSR investments. Prior work identifies a number of firm and managerial characteristics to explain firms' CSR investments. Cronqvist and Yu (2017) show that CEOs with daughters are associated with more investments in CSR. Davidson, Dey, and Smith (2019) find that firms led by materialistic CEOs are associated with low CSR investments. Shive and Foster (2020) find that independent private firms are less likely to pollute and incur penalties from the U.S. Environmental Protection Agency (EPA) than public firms. Using an international sample, Dyck et al. (2019) show that institutional ownership is positively associated with E&S performance, with additional tests suggesting this relation is causal. Starks, Venkat, and Zhu (2020) further note that investors with longer horizons tend to prefer firms with higher ESG scores significantly more than short-term investors do. Dyck et al. (2023) establish that governance changes, including the addition of a female director, are positively associated with corporate environmental performance.

2.2. Hypothesis development

Jensen and Meckling (1976) posit that equity analysts play an important governance role in mitigating agency costs associated with the separation of ownership and control due to these analysts' comparative advantages and specialization in monitoring related activities. Chen, Harford, and Lin (2015) further delineate at least two channels through which equity analysts serve their governance role: 1) they scrutinize firms' financial statements on a regular basis and interact with management during earnings conference calls and corporate site visits; and 2) they disseminate their research insights to institutional and retail investors via research reports and media interviews. Prior work shows that equity analysts help improve corporate governance and business operations (Yu 2008; Irani and Oesch 2013; Chen, Harford, and Lin 2015; Guo, Pérez-Castrillo, and Toldrà-Simats 2019; Bradley, Mao, and Zhang 2022).

In contrast to prior work, we focus on female equity analysts and their unique role in enhancing corporate E&S performance due to well-documented gender differences in values and willingness to delay gratification. Using a large general population survey in the U.S. over several decades, Beutel and Marini (1995) establish that women are more likely than men to express concern and responsibility for the well-being of others, less likely than men to accept materialism, and more likely than men to indicate that finding purpose and meaning in life is extremely important. Using a large international sample spanning 70 countries, Schwartz and Rubel (2005) find that benevolence values – the preservation and enhancement of the welfare of people with whom one is in frequent personal contact – are most important for women, followed by universalism – the understanding, appreciation, tolerance, and protection for the welfare of all people and for nature. In contrast, men consistently assign more importance to power, stimulation, hedonism, achievement, and self-direction values than women do.[5]

Prior work further suggests that relative to men, women have more prosocial and altruistic responses to, and preferences for, redistribution and equity (Bertrand 2011). Women in general are more supportive of social welfare, education, and health programs, and of economic policies that assist minority groups, the unemployed, and the poor (Shapiro and Mahajan 1986; Gilligan, Ward, and Taylor 1988). In addition, women are more likely than men to support policies that regulate and protect citizens, consumers, and the environment (Shapiro and Mahajan 1986). Miller (2008) finds that suffrage rights for women in U.S. states are associated with large increases in public health spending. Alesina and Giuliano (2011) find that women are more pro-redistribution than men.

[5] Using director surveys from Sweden, Adams and Funk (2012) confirm that female and male directors differ systematically in their core values: Female directors are more benevolent and universally concerned but less power-oriented than male directors.

Relatedly, experimental and survey evidence in psychology (Silverman 2003; Castillo et al. 2011) indicates that women, on average, are more patient and less impulsive than men when trading off present versus future values.

By nature, E&S investments are a long-term value-enhancing strategy that maximizes long-term shareholder value, and may not contribute to (and may even sacrifice) short-term stock performance (Krüger 2015; Ferrell, Hao, and Renneboog 2016). Gender differences in values and willingness to delay gratification reviewed above suggest that compared to male equity analysts, female equity analysts will be more likely to care and express their concerns about a firm's E&S performance.

On the other hand, several factors potentially prevent us from finding any significant association between the number of female analysts following a firm and that firm's E&S performance.

First, equity analysts share similar educational and professional backgrounds, which might help narrow gender differences in evaluating corporate fundamentals, including corporate E&S performance (Cohen, Frazzini, and Malloy 2010; Fang and Huang 2017). Second, consistent with the well-documented gender difference in overconfidence (Croson and Gneezy 2009), Comprix, Lopatta, and Tideman (2022) find that female analysts are less aggressive in asserting their views during conference calls than their male counterparts, which makes female analysts less likely to be heard.

We expect gender differences in values and willingness to delay gratification to prevail. Given analysts' information discovery and interpretation roles in capital markets, managers whose firms are followed by female analysts will pay more attention and invest more in E&S policies and practices compared to managers whose firms are not followed by female analysts.

Our main hypothesis is thus as follows: There is a positive association between a firm's female equity analyst following and that firm's E&S performance.

In terms of potential channels, analysts produce research reports that provide earnings forecasts and stock recommendations; they also appear in business media to discuss firms that they follow. Analysts could potentially use these opportunities to express concerns about these firms.[6] Given gender differences in values related to community and compassion, we expect that female analysts driven by a stronger intrinsic motivation pay more attention to E&S issues than their male counterparts. We thus hypothesize that one possible channel through which female equity analysts could help shape corporate E&S performance is via their reports, which feature more discussions on E&S issues than reports from male analysts, resulting in improved corporate E&S performance.

Analysts also often interact directly with management during earnings conference calls, and could use such opportunities to question aspects of a firm's business operations. Given gender differences in values as referenced above, we hypothesize that another possible channel through which female equity analysts could help shape corporate E&S performance is via earnings conference calls, during which female analysts raise more questions regarding a firm's E&S issues than their male counterparts, resulting in improved corporate E&S performance.

In summary, due to gender differences in values and willingness to delay gratification, we hypothesize that there is a positive association between a firm's female equity analyst following and that firm's E&S performance. We further posit that there are two possible mechanisms underlying our main hypothesis: 1) compared to their male counterparts, female

[6] Relatedly, Krüger, Sautner, Tang, and Zhong (2021) find that mandatory ESG disclosures increase analysts' forecast accuracy and reduce analysts' forecast dispersion, suggesting that analysts do pay attention to corporate E&S performance when making forecasts and recommendations.

analysts pay more attention to E&S issues in their reports; and 2) the same is true during conference calls.

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

3.1. Why FinBERT?

To capture analyst monitoring through their research activities, we develop a machine learning approach to extract 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 analyst reports) and questions (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 going through a large corpus of financial text (including annual/quarterly reports, analyst reports, and conference calls) and learning to predict randomly masked words and if two sentences are adjacent in a document. After pre-training, the 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.[7] 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 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 a high text classification accuracy.

[7] Classification features are the input features used by a machine learning model to predict the class (i.e., category) of a given text. These features are typically derived from the text itself and can include various types of information such as the words and phrases used. In the case of BERT, the contextualized embedding vector compresses information about the meaning of a word, the syntax of a sentence, and the context of a sentence within the larger document into a single vector.

In this paper, we fine-tune FinBERT to classify if sentences in the analyst reports or questions during earnings conference calls are related to E&S issues. In the context of analyst reports, our goal is to classify sentences into one of the following three categories: Environmental (E), Social (S), or neither (Non-E&S). In the context of conference calls, our goal is to classify analyst questions into the above three categories, as E&S-related issues often span multiple sentences within a question, and breaking them down into individual sentences would therefore result in the loss of valuable information.

Although Huang, Wang, and Yang (2023) have 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 is not ideal when applied to our two corpora. This limitation is likely because the language and style used to discuss ESG topics can vary significantly across different domains. 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 likely differs from the language used by analysts writing from a capital market professional's perspective, or from the more colloquial expressions used by analysts during Q&A sessions of earnings calls. To address these challenges, we propose to fine-tune the FinBERT model of Huang, Wang, and Yang (2023) using domain-specific training examples from analyst reports and earnings calls, which will help improve the model's accuracy to detect E&S-related discussions in these domains.

3.2. Constructing domain-specific training examples via active learning

In alignment with data centric-AI (DCAI) principles, we employ *active learning* – an algorithm that methodologically identifies a small set of important examples for labeling within a large amount of unlabeled data. This human-in-the-loop approach facilitates the efficient curation of domain-specific examples, thereby enabling the fine-tuning of two E&S text classification models, each specifically designed for analyst reports and conference calls.

Active learning embodies the iterative refinement ethos of DCAI, continuously improving a model's performance by refining its training data set.

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.[8] Sentences (in analyst reports) or questions (in conference calls) containing those keywords are tentatively labeled as positive examples (E or S), and random sentences (questions) are used as negative examples (Non-E&S). In Step 2, we use the initial training sample 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 sample. Given the *Noisy E&S model*'s output, a subset of important examples is labeled by human annotators (Cormack and Grossman 2014).[9] 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 step by step.

We find that after active learning, the model performance of E&S classification tasks improves significantly compared to the FinBERT-ESG, which Huang, Wang, and Yang (2023) fine-tuned using 2,000 labeled sentences from firms' CSR reports and MD&A sections of 10-K filings. In particular, 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 (conference calls). Intuitively, the improvement from our approach compared to prior approaches is attributed to the fact that our training data are more closely aligned with how analysts write (ask) about E&S issues in their reports (during conference calls).

[8] Table IA1 in the Internet Appendix lists queries of corporate E&S practices.
[9] Table IA2 in the Internet Appendix lists some important examples identified by active learning protocols for human labeling.

3.3. Capturing E&S-related discussions

We employ the fine-tuned FinBERT models to classify each sentence (question) in analyst reports (conference calls).[10] Based on classification results, we quantify both the frequency and intensity of discussions regarding E&S issues within analyst reports. For each report, 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 analysts discussing E&S issues by using the natural logarithm of one plus the number of sentences related to E&S in an analyst report (*Ln(1 + N_E&S sentences)*, *Ln(1 + N_E sentences)*, and *Ln(1 + N_S sentences)*). Much as we do with analyst reports, we measure both the frequency and intensity of questions asked by analysts related to E&S issues during calls. The key measures are defined analogously as those in the analyst report analysis.

Figures IA2 and IA3 in the Internet Appendix provide an overview of the temporal trends and industry distributions of E&S-related discussions in analyst reports and E&S-related questions during earnings conference calls. Figure IA2 reveals an overall upward trend in E&S discussions over the years. Notably, discussions pertaining to environmental issues in analyst 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 note that while analysts tend to write more about environment-related issues in their reports, they tend to raise more social-related questions during calls.[11] In terms of industry breakdown, it is not

[10] Table IA3 in the Internet Appendix provides examples of E&S-related sentences identified in analyst reports. Table IA4 in the Internet Appendix provides examples of E&S-related questions identified during earnings conference calls.
[11] 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 conference calls. Second, conference calls

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, Manufacturing, and Consumer Durables. In contrast, discussions of social issues exhibit a more even distribution across industries.

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 for each sentence.[12] We sample a total of 5,000 sentences from analyst reports and 5,000 questions from earnings 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/questions for each corpus, which provides a corpus-specific measure of the importance of each token in the text.

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 analyst reports, whereas pollution, climate, and greenhouse-related issues (e.g., *pollution, renewables, climate, greenhouse*) are more important during conference 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

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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.

[12] 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.

on broader topics. Community relations and discrimination-related issues (e.g., *community, sex, discriminations*) are given more emphasis in analyst reports, while corporate wrongdoing (e.g., *corruption*, *indigenous, violation*), and cybersecurity incidents (e.g., *hackers*) are more important during conference 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 choice of fine-tuning separate machine learning models for analyst reports and conference calls.

4. Sample Formation and Overview

4.1. Sample formation

Our key measure of corporate E&S performance comes from Refinitiv's ESG database (formally known as Thomson Reuters' ASSET4 database) (Dyck et al. 2019; Berg, Kölbel, and Rigobon 2022).[13] Their rank-based aggregate scores range from 0 to 1 and measure a firm's E&S performance relative to all other firms in the same industry group in a given year. For example, in the motor vehicles and motor vehicle equipment industry (SIC code 371), Ford Motor Company has an environmental score of 0.916 (ranked the 13th out of the 58 firms in the industry) and a social score of 0.971 (ranked the first) in 2020, making it the highest achiever in E&S performance in that year.

[13] According to Refinitiv (2022), they employ over 700 content research analysts trained to collect ESG data from a multitude of sources, spanning annual reports, corporate CSR reports, stock exchange filings, company websites, non-governmental organization websites, and news sources. There are a number of reasons for us to employ the Refinitiv ESG database for our analysis: 1) it has the broadest coverage of firms; 2) it has the longest time series and it is expected that the database will be continuously updated going forward; 3) it aggregates more than 700 ESG metrics and has comprehensive coverage of the majority of ESG dimensions, and 4) it is used by prior work, see, for example, Dyck et al. (2019), and hence it is easy for us to benchmark with prior work. For more details, see https://www.refinitiv.com/en/financial-data/company-data/esg-data. We are aware of some controversies associated with the Refinitiv ESG ratings (Berg, Koelbel, and Rigobon 2022), as well as some inconsistencies across various ESG data sets. For robustness checks, we also employ three other ESG data sets: Thomson Reuters's ASSET4 (discontinued after 2019), MSCI's KLD Stats, and Morningstar's Sustainalytics, and two measures of real E&S outcomes: carbon emissions and workplace safety misconduct cases.

Our Refinitiv data set was downloaded in April 2022 from WRDS. Our sample period starts in 2005 because the coverage of Capital IQ, which allows us to determine analyst gender, became more complete starting in 2004. Our sample period ends in 2021 because we employ a lead-lag specification in our regression analysis and E&S scores are available until 2021. We adjust the fiscal year information from Refinitiv to sync with that in the Compustat data set following Berg, Fabisik, and Sautner (2021). Table 1 lists the steps taken to form our main sample, comprising 20,423 firm-year observations representing 3,567 unique firms.

4.2. Identifying female equity analysts

From the Institutional Brokers Estimates System (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. 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 by 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. 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 (an 84.3% matching rate).[14]

4.3. Identifying female equity analysts in analyst reports

We download 1,681,153 reports by 11,464 analysts from 822 brokers covering 1,780 firms over the period 2004–2020 from Thomson One’s Investext.[15] 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.

To determine analyst gender in the analyst report sample, we match each analyst’s name in Investext to our hand-collected gender data in the I/B/E/S-Capital IQ merged sample as described in Section 4.2. 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.

[14] We rely on information from Capital IQ 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.

[15] Our sample in Section 3 includes 2,434,739 analyst reports covering S&P 1500 constituent firms over the period 2004–2020. 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.

After removing analyst reports with missing analyst-level control variables, our final sample comprises 965,377 reports covering 19,302 firm-year observations for 1,686 unique firms for the channel analysis.

4.4. Identifying female equity analysts during earnings conference calls

We download 64,075 earnings call transcripts covering 2,186 firms over the period 2007–2020 from Capital IQ.[16] We retain analysts' questions in the Q&A section of earnings conference calls. 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 4.3. 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 call-analyst observations with missing analyst-level control variables, our final sample comprises 225,450 call-analyst observations from 51,872 earnings conference calls covering 14,328 firm-year observations for 1,347 unique firms for the channel analysis.

4.5. 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.

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). Our key variable of interest is the number of female equity analysts covering a firm, *N_female*. The mean/median is 0.480 (0). About a third of firm-year observations in our sample have at least one female equity analyst

[16] Our sample in Section 3 includes 129,302 earnings calls covering firms that can be matched with Compustat over the period 2007–2020. The sample of 2,186 firms is a subset of our main sample of 3,567 firms, suggesting that 61% of firms in our main sample hold earnings conference calls (as far as we can identify).

following, and the average female ratio of analysts is 7.3%.[17] 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 2020).

Panel B of Table 2 provides the Pearson correlation matrix. We show that there is a positive association between *N_female* and three different measures of corporate E&S performance. Examination of the correlation matrix suggests that multicollinearity is unlikely to be an issue.

5. Main Results

5.1. Female equity analysts and corporate E&S performance

5.1.1. Using Refinitiv E&S scores

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

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

where the dependent variable is $E\&S\ score_{i,t+1}$, or its component scores – $E\ score_{i,t+1}$ and $S\ score_{i,t+1}$ of firm i in year $t+1$. The key variable of interest is the number of female analysts following a firm (*N_female).* The control variables largely follow Dyck et al. (2019), Chen, Dong, and Lin (2020), Starks, Venkat, and Zhu (2020) 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). In an alternative specification, we include firm and year fixed effects to control for time-invariant

[17] Given that our sample formation starts with Refinitiv's coverage to ensure data availability on E&S performance measures, it is worth noting that about a third of our sample firms do not have any analyst coverage. Conditional on having female analyst coverage, the average female ratio of analysts is 11%. In unreported analysis, we find that there is no time trend in the number of (female) analysts following our sample firms over the sample period 2004–2020.

firm unobservables and time trends that might drive both female analyst coverage and corporate E&S performance. Table 3 presents the regression results.

Columns (1), (3), and (5) of Panel A present the regression results including industry × year fixed effects. 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 expense item in selling, general and administrative expenses (SG&A) (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 reinforce our argument that female analysts have different values regarding E&S issues from male analysts.

In terms of other firm controls, there is a positive and significant association between *Firm size*, *Tobin's Q, ROA, SG&A,* and *E&S score*, and there is a negative and significant association between *Leverage, Cash holdings, CEO duality*, *Institutional ownership,* and *E&S score*.

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. This economic significance is comparable to other important factors identified in prior literature. For example, Dyck et al. (2019) find that a one-standard-deviation increase in a firm's institutional ownership (0.168) is associated with a 4.5% (0.168 × 0.268) increase in its environmental performance. This economic significance is also comparable to other control variables in our baseline regression. Using the regression specification with industry × year fixed effects as an example (column (1)), 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*.[18]

To examine 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 IA5 Panel C in the Internet Appendix 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.[19, 20]

To address potential endogeneity concerns, columns (2), (4), and (6) of Table 3 Panel A present the regression results including firm and year fixed effects. We show that there remains a positive and significant association between *N_female* and *E&S score*. In contrast,

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[18] As discussed earlier, we 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 the full analyst sample if the missing data problem in Capital IQ applies equally to both male and female equity analysts in the population. Our main findings remain (see Table IA5 Panels A and B in the Internet Appendix).

[19] 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. 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 IA5 Panel D 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.

[20] 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 IA5 Panel E in the Internet Appendix, we show that our main findings remain controlling for gender differences in general and/or firm-specific experience among following analysts.

the negative association between *Analyst coverage* and *E&S score* is significant in only two out of the three specifications at the ten percent level. One possible explanation for this finding is that analyst coverage tends to be sticky (the autocorrelation of analyst coverage is 0.88) and including firm fixed effects results in minimum variations in the analyst coverage variable.

E&S score is an equal weighted score of *E score* and *S score*, with the former a sum of three dimensions: Emissions Reduction, Innovation, and Resource Use; and the latter a sum of four: Community, Human Rights, Product Responsibility, and Workforce. We next examine the dimension(s) on which female analysts have a significant monitoring effect. Table 3 Panels B and C present the results. We show that with the exception of the Community dimension, there is a positive and significant association between *N_female* and the different dimension(s) of corporate E&S performance.

5.1.2. Using alternative E&S scores

Given the controversies and/or inconsistencies associated with different ESG ratings (e.g., Berg, Koelbel, and Rigobon 2022), Table IA6 in the Internet Appendix presents the regression results from our main specification in Equation (1) using alternative data sets to measure E&S performance. We employ data from three different ESG rating providers: Thomson Reuters' ASSET4,[21] MSCI's KLD Stats,[22] and Morningstar's Sustainalytics.[23] Our selection of two other data sets is guided by their market and academic relevance. We show that across all three alternative data sets, our main findings remain.

5.1.3. Using measures of real E&S outcomes

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[21] In 2018, Refinitiv acquired ASSET4 from Thomson Reuters and renamed and replaced it with Refinitiv's ESG ratings.

[22] In 2009, KLD, formerly known as Kinder, Lydenberg, Domini & Co., was acquired by RiskMetrics. In 2010, MSCI acquired RiskMetrics and renamed the legacy KLD database as MSCI's KLD Stats.

[23] We include Thomson Reuters' ASSET4 because Refinitiv's ESG ratings employ very different methodologies from those used by Thomson Reuters (Berg, Fabisik, and Sautner 2021).

To capture corporate real E&S outcomes, we employ carbon emissions data from S&P Global Trucost and workplace safety misconduct cases from Violation Tracker. Both measures are not subject to the common criticism associated with ESG ratings. We measure *Carbon emissions* as the natural logarithm of one plus the sum of annual Scope 1 and Scope 2 carbon emissions, following Sautner et al. (2023). The Violation Tracker data on workplace safety violation contains 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 misconduct cases. *Workplace safety-related penalties* is the natural algorithm of one plus the total dollar amount of penalty incurred due to a firm's workplace safety or health violations in a given year. *Workplace safety-related cases* is defined analogously.

Table 3 Panel D presents the results. 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 violations, and frequency of workplace safety violation cases. The evidence consistently suggests that a firm's female analyst following 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 analyst monitoring corporate E&S performance but do not otherwise, correlate with corporate E&S performance. According to Kelly and Ljungqvist (2012), broker closures are largely driven by their business operations, such as competitive pressure, strategic considerations, and/or regulation, rather than the characteristics of firms covered by their analysts.[24] As far as we are aware, we are one of the first in the literature to use broker closures to create an exogenous drop in the number of female analysts covering a firm.

To identify broker closures over the period 2005−2019, we proceed as follows.[25] 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.[26] 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.[27]

5.2.2. Identifying the treated and control firms

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[24] We do not consider broker closures due to mergers because analyst retention and their stock coverage decisions are determined by analyst and/or firm characteristics (McNichols and O'Brien 1997; Wu and Zang 2009).

[25] 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.

[26] 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 only include 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.

[27] As a result, the sample period for the DID analysis ends in 2017 as broker closures after 2017 only affected male analysts.

To form the treated firm sample, following Kelly and Ljungqvist (2012) and Cen, Chen, Dasgupta, and Ragunathan (2021), we first identify analysts who work 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.[28] On average, a closure event affects 55 analysts, comprising 7 female analysts and 48 male analysts. We then merge firms covered by those exited brokers with the baseline sample of 20,423 firm-year observations in Table 3 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.[29] Finally, we keep only firms that are previously covered by a female analyst and hence will lose such coverage due to broker closure.[30] 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 IA7 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 sample broker closures on average involve two female analysts and sample female analysts on average cover three firms, and that sample broker closures do not cluster in specific industries.

[28] 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 Kecskes 2013) and use a six-month "event period" (denoted *t*) centered around a broker's closure date.

[29] 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.

[30] 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.

To identify the control firms, we first remove the treated firms from the baseline sample in Table 3 and retain only firms that have non-missing E&S scores and 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.[31] Our final matched sample consists of 105 (1,197) treated (control) firms for a total of 2,604 (= 2 × (105 + 1,197)) firm-year observations.

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:

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

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.

[31] 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).

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 drop in female analyst coverage of their previously covered firms. Panel B presents 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 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 following due to broker closures) decreases by 7.3% (0.024/0.331) relative to the mean, compared to the matched control firms (without experiencing a drop in female and/or male analyst coverage). Overall, the DID analysis suggests that there is a causal effect of female analyst coverage on firm-level E&S performance.

In supplemental analysis, we conduct a falsification test to ensure the treatment effect identified in Panel B is not spurious. We repeat the DID analysis by using a sample of pseudo treated firms, i.e., firms that lost coverage from a male analyst due to the same closure events, and the same control firms as in Panel B. Table 4 Panel C 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 lose male analyst coverage.

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

6. The Channel Analysis

In this section, we explore the possible channels through which female equity analysts help enhance corporate E&S performance. Specifically, we apply our fine-tuned FinBERT models described in Section 3 to capture analysts' discussions of E&S issues in analyst reports and during earnings conference calls.

6.1. Analyst reports

Table 5 Panel A presents the summary statistics at the analyst 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 an analyst report is 0.9. Analysts are more likely to write about environmental issues than social issues. The probability for the former is 22.1%, whereas the probability for the latter is 13.4%.

Panels B presents the regression analysis at the analyst 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 1.4 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 4.7% (1.4%/29.6%) increase.

6.2. Earnings conference calls

Table 6 Panel A presents the summary statistics at the call-analyst level. We show that 15.3% of the analysts ask about firms' E&S issues during earnings conference calls; and the average number of E&S-related questions in a call is 0.2. Analysts are more likely to ask questions about social issues than environmental issues. The probability of the former is 12.1%, whereas the probability of the latter is 3.9%.

Panel B presents the regression analysis at the call-analyst 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.[32]

Finally, we 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. Table IA8 presents the results. 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)*,

[32] 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/questions. At the sentence level (question 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. In untabulated analysis, we find no significant association between an analyst being a female and her tone discussing E&S issues in her reports or during calls.

Ln(1 + N_E&S questions), *Ln(1 + N_E questions)*, and *Ln(1 + N_S questions)* are defined analogously. We first show that there is a positive and significant association between E&S discussions in either channel 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.

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 hypothesize that the voices of female analysts regarding corporate E&S performance are 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). General experience is the number of years since an analyst first appeared in the I/B/E/S Detail History file. Firm experience is the number of years since an analyst first made an earnings forecast of a focal firm in a given year.[33] *Female more general experience* is an indicator variable that takes the

[33] For this analysis, our sample size is reduced because we require the I/B/E/S Detail History file to capture analyst experience.

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. *Female more firm experience* is defined analogously. *Female star analyst* is an indicator variable that takes the value of one if at least one of a firm's female analysts has All-Star status in a given year, and zero otherwise. Table 7 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. Interestingly, we 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 above on gender differences in values, we would expect that the presence of female directors and officers could play a similar role in enhancing corporate E&S performance. Table IA9 in the Internet Appendix presents the results from examining female directors/executives as well as their potential interaction effects with female analysts.

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*. Interestingly, we 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. Note that our sample size is reduced because data on the gender of executives is from ExecuComp, which covers only S&P 1500 constituents. 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. [34]

In summary, the results in Table IA9 help support our hypothesis that female analysts play a unique role in monitoring firms' E&S practices.

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

Career concerns play a central role in analysts' allocation of effort (Harford, Jiang, Wang, and Xie 2019). The positive association between female analysts following and that firm's E&S performance may reflect these analysts' career concerns instead of gender

[34] 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*.

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 E&S discussions/questions in analyst reports/conference calls by female analysts and their likelihood of achieving All-Star status 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. Following Clement (1999), we measure *Forecast accuracy* as 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. To examine the relationship between E&S discussions and an analyst's career outcomes, we first calculate the firm-analyst-year level measures by taking the average of the report level and the call-analyst level variables of E&S discussions in Tables 5 and 6, respectively. We then apply the logarithmic transformation to get the intensity measures, *Ln(1 + N_E&S sentences)* and *Ln(1 + N_E&S questions)*. Our analysis is at the firm-analyst-year level.

Table IA10 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 main hypothesis that gender differences in values are the main driver of the monitoring role of female equity analysts in corporate E&S performance.

7.4. Female equity analysts and corporate governance performance

Given the discussion above on gender differences in values, we expect that female analysts will not play any unique role in improving corporate governance performance. Table

IA11 in the Internet Appendix presents the results examining the relation between female analyst coverage and corporate governance performance (*G score*) and its sub-scores on *CSR Strategy*, *Management*, and *Shareholders*. Columns (1), (3), (5), and (7) present the regression results including industry × year fixed effects. We show that there is no significant association between *N_female* and *G score* or its sub-scores, with one exception: when the dependent variable is *CSR Strategy*. Columns (2), (4), (6), and (8) present the regression results including firm and year fixed effects. Again, we show that there is no significant association between *N_female* and *G score* or its sub-scores.

8. Conclusions

Using a novel sample of over 10,000 sell-side equity analysts with gender data and the Refinitiv ESG database 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 DID regression results show that female analyst coverage has a causal effect on firms' E&S performance.

To delineate the channels through which female analysts help improve corporate E&S performance, we first apply an active learning approach to fine-tune FinBERT – a pre-trained large language model – using domain-specific E&S discussions. We then use the fine-tuned models to sift through 2.4 million analyst reports and over 120,000 earnings call transcripts to uncover E&S-related discussions in analyst 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. Moreover, 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. We conclude that female equity analysts play a significant monitoring role in enhancing corporate E&S performance.

Our study combines active learning with FinBERT, thereby introducing an efficient, data-centric approach to fine-tuning large language models for specialized tasks in finance and accounting. To the best of our knowledge, our study is one of the first in the literature to develop a text-based measure of firms' social exposure. Our firm-year level measures of E&S exposure, viewed through analysts' lens, can offer fresh insights for future research on the ESG-value relationship. Collectively, by leveraging the most extensive collection of analyst data to date, both structured and unstructured, our study underscores the significant influence female equity analysts exert over firms' E&S performance.

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.
E score	The environmental performance score in a given year. The rank-based score measures a firm's environmental performance relative to all other firms in the same industry group (following Thomson Reuters Business Classification (TRBC)) in a given year.
S score	The social performance score in a given year. The rank-based score measures a firm's social performance relative to all other firms in the same industry group (following Thomson Reuters Business Classification (TRBC)) in a given year.
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 millions 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.
Emissions reduction	The environmental performance sub-score regarding a firm's commitment and effectiveness towards reducing environmental emissions in its production and operational processes in a given year.
Innovation	The environmental performance sub-score regarding a firm's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes, or eco-designed product in a given year.
Resource use	The environmental performance sub-score regarding a firm's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management in a given year.
Community	The social performance sub-score regarding a firm's commitment to being a good citizen, protecting public health and respecting business ethics in a given year.

Human rights	The social performance sub-score regarding a firm's effectiveness in terms of respecting fundamental human rights conventions in a given year.
Product responsibility	The social performance sub-score regarding a firm's capacity to produce quality goods and services, integrating the customer's health and safety, integrity and data privacy in a given year.
Workforce	The social performance sub-score regarding a firm's effectiveness in terms of providing job satisfaction, a healthy and safe workplace, maintaining diversity and equal opportunities and development opportunities for its workforce in a given year.
Carbon emissions	Natural logarithm of one plus the sum of annual Scope 1 and Scope 2 carbon emissions (metric tons of CO2) in a given year following Sautner et al. (2023). Scope 1 emissions originate from the combustion of fossil fuels or releases during manufacturing. Scope 2 emissions originate from the purchase of electricity, heating, or cooling.
Workplace safety-related penalties	Natural algorithm of one plus the total dollar amount of penalty incurred due to a firm's workplace safety or health violations in a given year.
Workplace safety-related cases	Natural algorithm of one plus the total number of workplace safety or health violations in a given year.
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 + 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.
G score	The governance performance score in a given year. The rank-based score measures a firm's governance performance relative to all other firms in the same industry group (following Thomson Reuters Business Classification (TRBC)) in a given year.
CSR strategy	The governance performance sub-score regarding a firm's practices to communicate that it integrates economic (financial), social and environmental dimensions into its day-to-day decision-making processes in a given year.
Management	The governance performance sub-score regarding a firm's commitment and effectiveness towards following best practice corporate governance principles in a given year.
Shareholders	The governance performance sub-score regarding a firm's effectiveness towards equal treatment of shareholders and the use of anti-takeover devices 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 showing up 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 showing up 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 showing up in an analyst report, and zero otherwise.
Ln(1 + N_E&S sentences)	Natural logarithm of one plus the count of E&S-related sentences in an analyst report.
Ln(1 + N_E sentences)	Natural logarithm of one plus the count of environmental-related sentences in an analyst report.
Ln(1 + N_S sentences)	Natural logarithm of one plus the count of social-related sentences in an analyst report.
N_sentences	The number of 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.
Call-analyst 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 count 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 count 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 count 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 level	
Forecast frequency	Number of annual EPS forecasts made by an analyst in a given year.
Forecast horizon	Average number of days between forecast dates of an analyst in a given year to the date of the annual earnings announcement.
# 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 for which an analyst makes at least one forecast of any firm in a given year.
Ln(Brokerage size)	Natural logarithm of brokerage size in a brokerage-year. Broker size is measured as the number of analysts making at least one forecast at the focal brokerage in a given year.
Firm-analyst-year level	
Star analyst	An indicator variable that takes the value of one if an analyst is accredited to All-Star status, and zero otherwise.
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.
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 a sample overview. 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. Panel A provides the summary statistics. Panel B presents the correlations for variables employed in the baseline regression. 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.

Panel A: Summary statistics for E&S performance and firm characteristics

	Mean	5th Percentile	Median	95th 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
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
Emission	0.261	0.000	0.114	0.890	0.311
Innovation	0.168	0.000	0.000	0.810	0.273
Resource use	0.272	0.000	0.110	0.908	0.322
Community	0.606	0.177	0.623	0.962	0.241
Human rights	0.192	0.000	0.000	0.857	0.296
Product responsibility	0.386	0.000	0.330	0.895	0.274
Workforce	0.419	0.055	0.379	0.902	0.262

Panel B: The correlation matrix

Variables	E&S score	E score	S score	N_female	Analyst coverage	Firm size	Tobin’s Q	ROA	Leverage	SG&A	Cash holdings	Tangibility	Board independence	CEO duality	Institutional ownership
E&S score	1														
E score	0.957[a]	1													
S score	0.951[a]	0.821[a]	1												
N_female	0.197[a]	0.182[a]	0.195[a]	1											
Analyst coverage	0.217[a]	0.197[a]	0.218[a]	0.562[a]	1										
Firm size	0.559[a]	0.514[a]	0.555[a]	0.269[a]	0.346[a]	1									
Tobin’s Q	-0.072[a]	-0.073[a]	-0.065[a]	0.087[a]	0.121[a]	-0.321[a]	1								
ROA	0.245[a]	0.214[a]	0.255[a]	0.130[a]	0.161[a]	0.330[a]	-0.052[a]	1							
Leverage	0.094[a]	0.108[a]	0.070[a]	-0.009	0.046[a]	0.151[a]	-0.099[a]	0.067[a]	1						
SG&A	-0.145[a]	-0.134[a]	-0.143[a]	0.066[a]	0.059[a]	-0.457[a]	0.551[a]	-0.351[a]	-0.162[a]	1					
Cash holdings	-0.177[a]	-0.160[a]	-0.179[a]	0.021[a]	0.038[a]	-0.363[a]	0.506[a]	-0.444[a]	-0.251[a]	0.591[a]	1				
Tangibility	0.077[a]	0.080[a]	0.066[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			
Board independence	-0.205[a]	-0.186[a]	-0.206[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		
CEO duality	0.062[a]	0.057[a]	0.062[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	
Institutional ownership	0.142[a]	0.125[a]	0.147[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]	1

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. The sample consists of 20,423 firm-year observations (representing 3,567 firms) with data on corporate E&S performance over the period 2005–2021. 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 firms' environmental performance sub-scores. Panel C examines the relation between female analyst coverage and firms' social performance sub-scores. Panel D examines the relation between female analyst coverage and corporate real E&S outcomes. *Caron emissions* is the natural logarithm of one plus the sum of annual Scope 1 and Scope 2 carbon emissions (metric tons of CO2) in a given year following Sautner et al. (2023). *Workplace safety-related penalties* is the natural algorithm of one plus the total dollar amount of penalty incurred due to a firm's workplace safety or health violations in a given year. *Workplace safety-related cases* is defined analogously. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent 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

Variable	E&S score (1)	E&S score (2)	E score (3)	E score (4)	S score (5)	S score (6)
N_female	0.014***	0.004**	0.017***	0.005**	0.010***	0.003
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)
Analyst coverage	-0.011**	-0.006*	-0.012**	-0.008*	-0.011**	-0.004
	(0.005)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)
Firm size	0.125***	0.052***	0.128***	0.050***	0.122***	0.053***
	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.006)
Tobin's Q	0.011***	-0.000	0.011***	-0.001	0.012***	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ROA	0.057***	0.012	0.018	0.008	0.096***	0.016
	(0.018)	(0.018)	(0.019)	(0.021)	(0.019)	(0.019)
Leverage	-0.070***	-0.022	-0.067***	-0.017	-0.074***	-0.027
	(0.017)	(0.017)	(0.018)	(0.020)	(0.018)	(0.018)
SG&A	0.131***	0.050***	0.130***	0.042*	0.133***	0.058***
	(0.018)	(0.018)	(0.020)	(0.021)	(0.019)	(0.019)
Cash holdings	-0.062***	-0.015*	-0.049***	-0.016	-0.074***	-0.014
	(0.012)	(0.008)	(0.013)	(0.010)	(0.012)	(0.009)
Tangibility	-0.010	-0.058***	0.006	-0.047***	-0.026	-0.070***
	(0.015)	(0.014)	(0.017)	(0.016)	(0.016)	(0.015)
Board independence	0.007	0.038	-0.008	0.006	0.022	0.071**
	(0.032)	(0.026)	(0.036)	(0.029)	(0.032)	(0.029)
CEO duality	-0.013**	-0.009*	-0.012*	-0.009	-0.015**	-0.009*
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)
Institutional ownership	-0.023**	0.030**	-0.040***	0.003	-0.007	0.058***
	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)	(0.013)
Constant	-0.604***	-0.026	-0.619***	0.023	-0.589***	-0.075
	(0.034)	(0.049)	(0.038)	(0.059)	(0.034)	(0.051)
Industry × Year FE	YES		YES		YES	
Firm FE		YES		YES		YES
Year FE		YES		YES		YES
Adjusted R^2	0.559	0.833	0.522	0.806	0.514	0.793
No. of observations	20,402	19,990	20,402	19,990	20,402	19,990

Panel B: Female analysts and corporate environmental performance sub-scores

Variable	Emissions reduction (1)	Innovation (2)	Resource use (3)
N_female	0.019***	0.013***	0.015***
	(0.005)	(0.005)	(0.005)
Analyst coverage	-0.017***	-0.000	-0.013**
	(0.006)	(0.006)	(0.006)
Firm size	0.131***	0.073***	0.136***
	(0.003)	(0.004)	(0.003)
Tobin's Q	0.012***	0.009***	0.009***
	(0.003)	(0.002)	(0.003)
ROA	0.009	-0.038*	0.025
	(0.021)	(0.020)	(0.021)
Leverage	-0.074***	-0.063***	-0.078***
	(0.019)	(0.018)	(0.020)
SG&A	0.131***	0.068***	0.165***
	(0.022)	(0.021)	(0.022)
Cash holdings	-0.038***	-0.025**	-0.055***
	(0.014)	(0.013)	(0.014)
Tangibility	0.021	-0.025	-0.021
	(0.018)	(0.017)	(0.018)
Board independence	-0.049	0.015	-0.066*
	(0.039)	(0.038)	(0.038)
CEO duality	-0.008	-0.006	-0.011
	(0.007)	(0.007)	(0.007)
Institutional ownership	-0.037***	-0.053***	-0.024*
	(0.014)	(0.015)	(0.014)
Constant	-0.769***	-0.411***	-0.778***
	(0.041)	(0.046)	(0.040)
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.460	0.323	0.483
No. of observations	20,402	20,402	20,402

Panel C: Female analysts and corporate social performance sub-scores

Variable	Community (1)	Human rights (2)	Product responsibility (3)	Workforce (4)
N_female	0.002	0.018***	0.010**	0.010**
	(0.003)	(0.005)	(0.005)	(0.004)
Analyst coverage	0.009**	-0.018***	-0.000	-0.007
	(0.004)	(0.005)	(0.005)	(0.005)
Firm size	0.083***	0.095***	0.066***	0.106***
	(0.002)	(0.004)	(0.003)	(0.003)
Tobin's Q	0.008***	0.005*	0.009***	0.021***
	(0.002)	(0.003)	(0.003)	(0.002)
ROA	0.024	0.097***	0.042*	-0.013
	(0.020)	(0.022)	(0.024)	(0.021)
Leverage	-0.038**	-0.045**	-0.049**	-0.066***
	(0.016)	(0.020)	(0.020)	(0.018)
SG&A	0.117***	0.126***	0.071***	0.078***
	(0.017)	(0.020)	(0.024)	(0.020)
Cash holdings	-0.043***	-0.038***	-0.043***	-0.003

	(0.011)	(0.013)	(0.014)	(0.013)
Tangibility	-0.015	-0.054***	-0.033*	-0.001
	(0.015)	(0.017)	(0.020)	(0.017)
Board independence	0.071**	-0.011	0.063*	0.022
	(0.028)	(0.036)	(0.037)	(0.032)
CEO duality	0.006	-0.010	0.001	-0.009
	(0.006)	(0.007)	(0.008)	(0.006)
Institutional ownership	0.042***	0.013	0.009	-0.002
	(0.012)	(0.014)	(0.014)	(0.013)
Constant	-0.190***	-0.579***	-0.220***	-0.500***
	(0.031)	(0.041)	(0.042)	(0.035)
Industry × Year FE	YES	YES	YES	YES
Adjusted R^2	0.327	0.367	0.226	0.365
No. of observations	20,402	20,402	20,402	20,402

Panel D: Female analysts and corporate real E&S outcomes

Variable	Carbon emissions (1)	Workplace safety-related penalties (2)	Workplace safety-related cases (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	1.869**	-0.344***	-2.783***
	(0.730)	(0.064)	(0.473)
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.526	0.246	0.242
No. of observations	20,402	20,402	20,402

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. The sample consists of 2,604 firm-year observations (210 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 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 in female analyst coverage due to broker closures on corporate E&S performance. Panel C examines the effect of a drop in male analyst coverage due to broker closures on corporate E&S performance. The treated firms in this analysis are those that experience a drop only in male analyst coverage due to broker closures. 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 in male analyst coverage due to broker closures, and zero otherwise. Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent 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	0.787***
	(0.019)
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 E&S performance

	E&S score	E score	S score
Variable	(1)	(2)	(3)
Treated × Post	-0.024**	-0.023*	-0.025*
	(0.012)	(0.014)	(0.015)
Post	0.009	0.009	0.010
	(0.006)	(0.007)	(0.007)
Analyst coverage	0.022*	0.020	0.025
	(0.013)	(0.015)	(0.018)
Firm size	0.055**	0.033	0.076***
	(0.023)	(0.028)	(0.026)
Tobin's Q	0.003	0.002	0.004
	(0.005)	(0.006)	(0.006)
ROA	-0.054	-0.092	-0.016
	(0.067)	(0.079)	(0.077)
Leverage	-0.127*	-0.148	-0.106
	(0.077)	(0.106)	(0.083)
SG&A	-0.041	-0.080	-0.002
	(0.081)	(0.097)	(0.078)
Cash holdings	-0.002	-0.001	-0.004
	(0.013)	(0.016)	(0.015)
Tangibility	-0.016	0.035	-0.067
	(0.068)	(0.081)	(0.076)
Board independence	-0.083	-0.154	-0.012

	(0.125)	(0.121)	(0.150)
CEO duality	-0.037*	-0.037*	-0.036
	(0.022)	(0.021)	(0.026)
Institutional ownership	0.032	-0.075	0.138***
	(0.053)	(0.080)	(0.052)
Constant	0.081	0.377	-0.215
	(0.238)	(0.286)	(0.243)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adjusted R^2	0.916	0.901	0.895
No. of observations	2,604	2,604	2,604

Panel C: 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)
Analyst coverage	0.007	0.011*	0.003
	(0.005)	(0.006)	(0.006)
Firm size	0.061***	0.049**	0.072***
	(0.016)	(0.019)	(0.015)
Tobin's Q	0.003	0.005	0.002
	(0.004)	(0.004)	(0.003)
ROA	0.030	0.031	0.029
	(0.035)	(0.045)	(0.038)
Leverage	-0.073**	-0.060	-0.087**
	(0.034)	(0.041)	(0.042)
SG&A	0.016	0.008	0.025
	(0.032)	(0.040)	(0.033)
Cash holdings	0.002	0.001	0.004
	(0.007)	(0.008)	(0.007)
Tangibility	-0.061*	-0.057	-0.064
	(0.033)	(0.042)	(0.042)
Board independence	0.044	-0.018	0.105
	(0.067)	(0.079)	(0.066)
CEO duality	-0.013	-0.015	-0.011
	(0.009)	(0.011)	(0.011)
Institutional ownership	0.033	0.022	0.045
	(0.025)	(0.034)	(0.028)
Constant	-0.171	-0.045	-0.297**
	(0.148)	(0.180)	(0.140)
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

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 from Thomson One's Investext database analyst reports over the period 2004–2020. We then match analyst reports with our analyst gender data set by using broker name and analyst full name. Our sample consists of 965,377 reports covering 19,302 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 showing up 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 count 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. Heteroskedasticity-consistent 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	5th Percentile	Median	95th Percentile	SD
Having E&S sentences	29.592	0.000	0.000	100.000	45.646
Having E sentences	22.145	0.000	0.000	100.000	41.523
Having S sentences	13.371	0.000	0.000	100.000	34.034
N_E&S sentences	0.919	0.000	0.000	4.000	3.350
Ln(1 + N_E&S sentences)	0.341	0.000	0.000	1.609	0.618
N_E sentences	0.645	0.000	0.000	3.000	2.804
Ln(1 + N_E sentences)	0.247	0.000	0.000	1.386	0.537
N_S sentences	0.274	0.000	0.000	2.000	1.293
Ln(1 + N_S sentences)	0.129	0.000	0.000	1.099	0.368
N_sentences	69.415	13.000	57.000	159.000	55.681
Female	0.111	0.000	0.000	1.000	0.314

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

Variable	Having E&S sentences (1)	Having E sentences (2)	Having S sentences (3)	Ln(1 + N_E&S sentences) (4)	Ln(1 + N_E sentences) (5)	Ln(1 + N_S sentences) (6)
Female	1.436***	0.894***	0.743***	0.014***	0.010**	0.005*
	(0.353)	(0.309)	(0.260)	(0.005)	(0.005)	(0.003)
Forecast frequency	-0.360***	-0.302***	-0.248***	-0.008***	-0.006***	-0.003***
	(0.039)	(0.036)	(0.029)	(0.001)	(0.001)	(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	-0.007	0.005	-0.010	-0.000	0.000	-0.000
	(0.022)	(0.020)	(0.015)	(0.000)	(0.000)	(0.000)
# industries followed	0.355***	0.319***	0.060	0.004***	0.003***	0.000
	(0.083)	(0.076)	(0.060)	(0.001)	(0.001)	(0.001)
General experience	0.010	-0.022	0.025	0.000	0.001	0.000
	(0.031)	(0.025)	(0.024)	(0.000)	(0.000)	(0.000)
Ln(Brokerage size)	28.252***	20.614***	13.483***	0.324***	0.225***	0.132***
	(0.726)	(0.667)	(0.483)	(0.011)	(0.009)	(0.006)
Constant	1.436***	0.894***	0.743***	0.014***	0.010**	0.005*
	(0.353)	(0.309)	(0.260)	(0.005)	(0.005)	(0.003)

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	0.159	0.298	0.350	0.171
No. of observations	965,377	965,377	965,377	965,377	965,377	965,377

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 from Capital IQ earnings call transcripts over the period 2007–2020. 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 225,450 call-analyst observations from 51,872 earnings conference calls covering 14,328 firm-year observations (representing 1,347 unique firms). At the call-analyst level, we capture E&S-related questions during a firm's earnings conference 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 firm's earnings conference call, and zero otherwise. We also capture the intensity of E&S questions by using the natural logarithm of one plus the count of relevant questions by an analyst during a firm's earnings conference 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 call-analyst level. Panel B presents the call-analyst-level regressions examining the relation between analyst gender and their E&S-related questions during earnings conference calls. Definitions of the variables are provided in the Appendix. Heteroskedasticity-consistent 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 call-analyst level

	Mean	5th Percentile	Median	95th Percentile	SD
Having E&S questions	15.314	0.000	0.000	100.000	36.012
Having E questions	3.944	0.000	0.000	0.000	19.463
Having S questions	12.050	0.000	0.000	100.000	32.554
N_E&S questions	0.184	0.000	0.000	1.000	0.473
Ln(1 + N_E&S questions)	0.118	0.000	0.000	0.693	0.286
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	0.139	0.000	0.000	1.000	0.402
Ln(1 + N_S questions)	0.091	0.000	0.000	0.693	0.250
N_questions	2.981	1.000	3.000	6.000	1.893
Female	0.121	0.000	0.000	1.000	0.326

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

Variable	Having E&S questions (1)	Having E questions (2)	Having S questions (3)	Ln(1 + N_E&S questions) (4)	Ln(1 + N_E questions) (5)	Ln(1 + N_S questions) (6)
Female	1.016***	0.253*	0.720***	0.008***	0.002*	0.006***
	(0.277)	(0.139)	(0.248)	(0.002)	(0.001)	(0.002)
Forecast frequency	0.074*	0.039*	0.043	0.001**	0.000**	0.000
	(0.039)	(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	0.032*	0.023***	0.016	0.000**	0.000***	0.000
	(0.017)	(0.009)	(0.016)	(0.000)	(0.000)	(0.000)
# industries followed	-0.114*	-0.043	-0.104*	-0.001*	-0.000	-0.001*
	(0.067)	(0.036)	(0.059)	(0.001)	(0.000)	(0.000)
General experience	0.130***	0.027**	0.117***	0.001***	0.000***	0.001***
	(0.021)	(0.011)	(0.019)	(0.000)	(0.000)	(0.000)
Ln(Brokerage size)	13.227***	3.222***	10.460***	0.098***	0.023***	0.077***
	(0.590)	(0.306)	(0.527)	(0.005)	(0.002)	(0.004)

Constant	1.016***	0.253*	0.720***	0.008***	0.002*	0.006***
	(0.277)	(0.139)	(0.248)	(0.002)	(0.001)	(0.002)
Firm × Year FE	YES	YES	YES	YES	YES	YES
Broker × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.095	0.136	0.090	0.110	0.150	0.104
No. of observations	225,450	225,450	225,450	225,450	225,450	225,450

Table 7
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. Heteroskedasticity-consistent 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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.561	0.524	0.515
No. of observations	20,402	20,402	20,402

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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.562	0.525	0.517
No. of observations	20,402	20,402	20,402

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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.561	0.524	0.516
No. of observations	20,402	20,402	20,402

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 and 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 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 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 IA1 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 Operator 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 IA1 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 IA2 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 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 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 conference calls. For conference 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% to 58%, and the fraction of calls discussing social issues ranges between 7% to 45% (Raman, Bang, and Nourbakhsh 2020; Chava, Du, and Malakar 2021).

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Figure IA1
Active Learning Flowchart

This figure presents a flowchart of the active learning process.

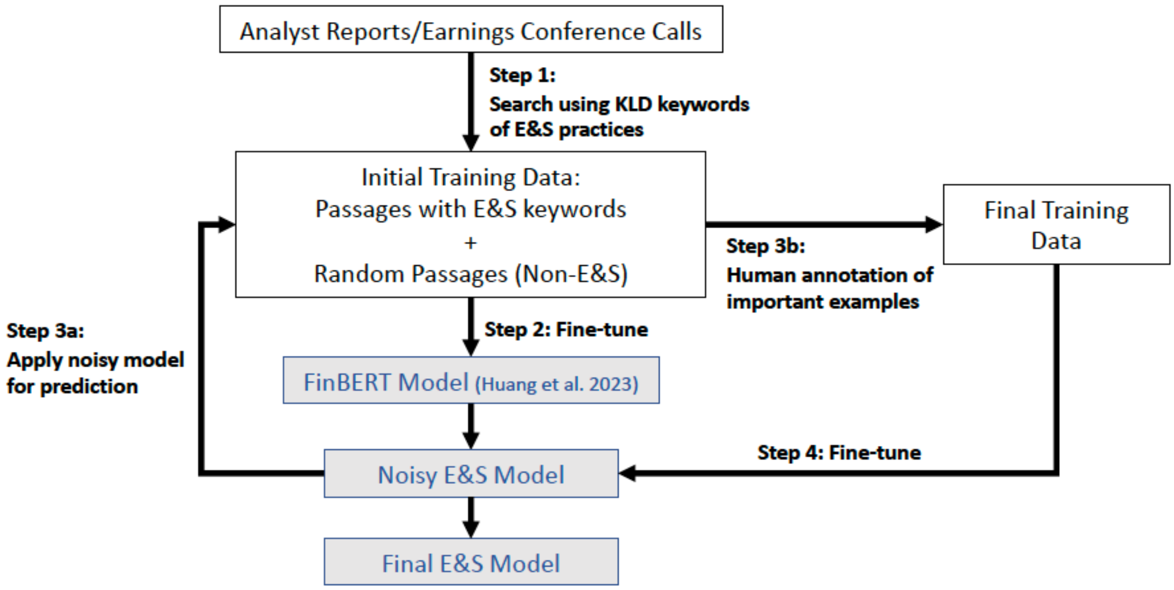


Figure IA2
Temporal trends in E&S-related discussions in analyst reports and during earnings conference calls

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 from Thomson One's Investext database over the period 2004–2020, and earnings call transcripts from Capital IQ over the period 2007–2020. 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.

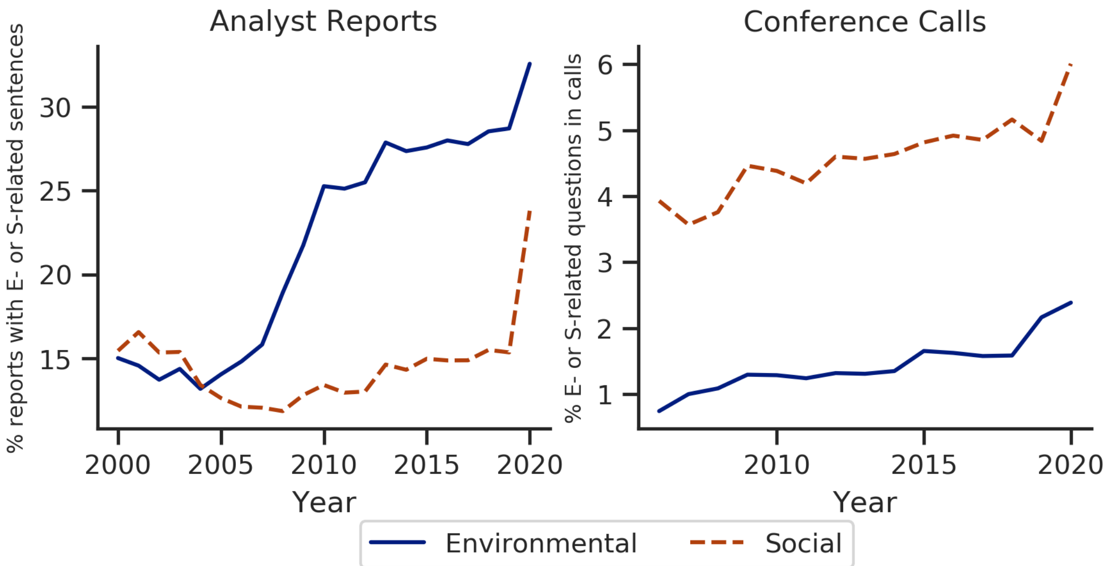


Figure IA3
Distribution of E&S-related discussions in analyst reports and during earnings conference calls across Fama-French 12 industries

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 from Thomson One's Investext database over the period 2004–2020, and earnings call transcripts from Capital IQ over the period 2007–2020. 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.

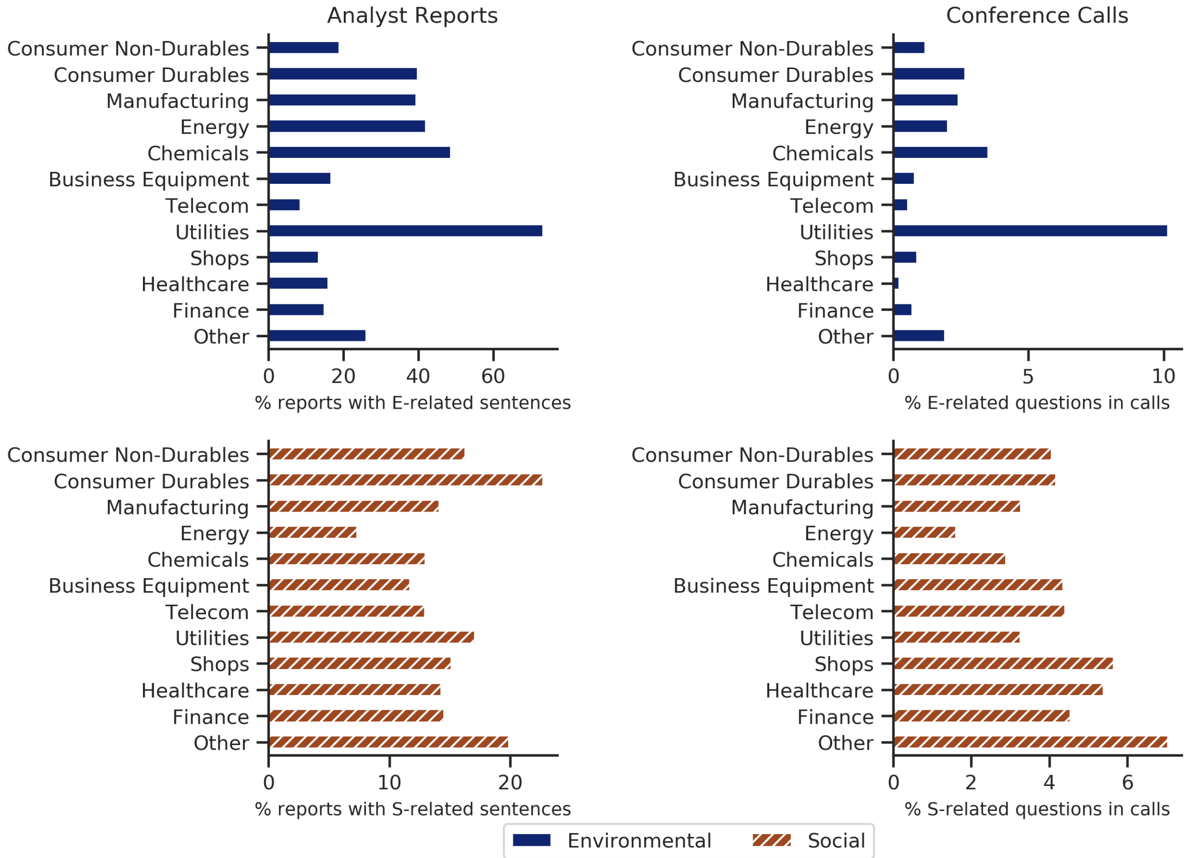
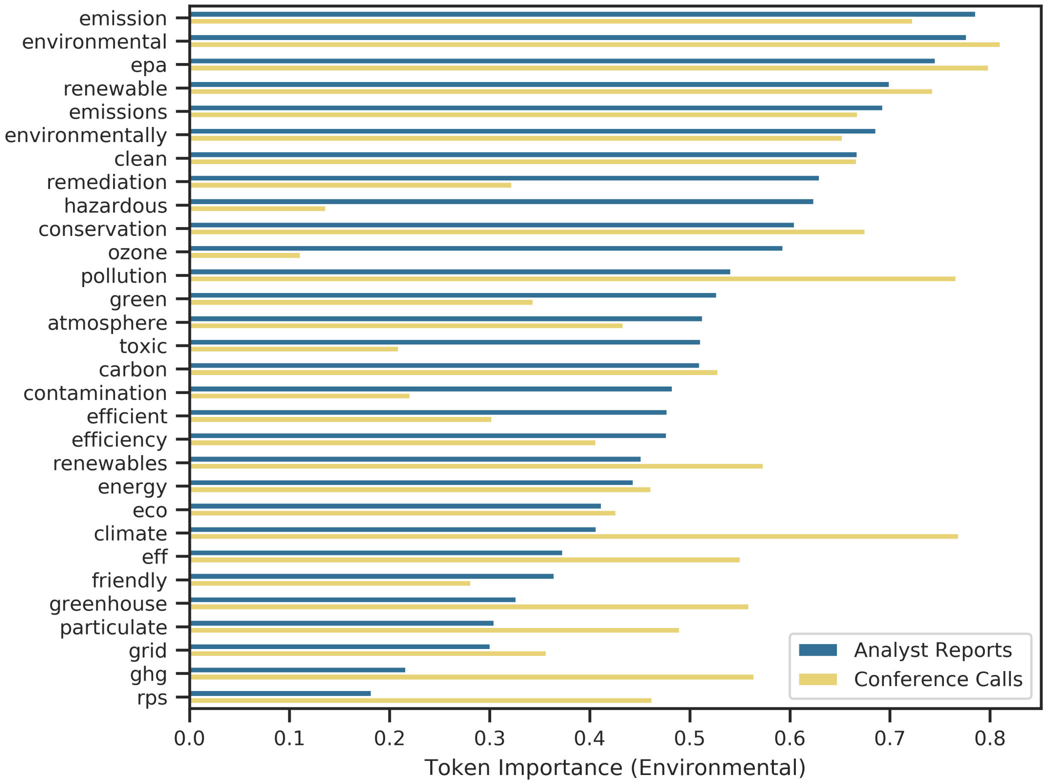


Figure IA4
Most important tokens in fine-tuned FinBERT models

This figure lists the most important tokens from our fine-tuned FinBERT models. We obtain analyst reports from Thomson One's Investext database over the period 2004–2020, and earnings call transcripts from Capital IQ over the period 2007–2020. 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

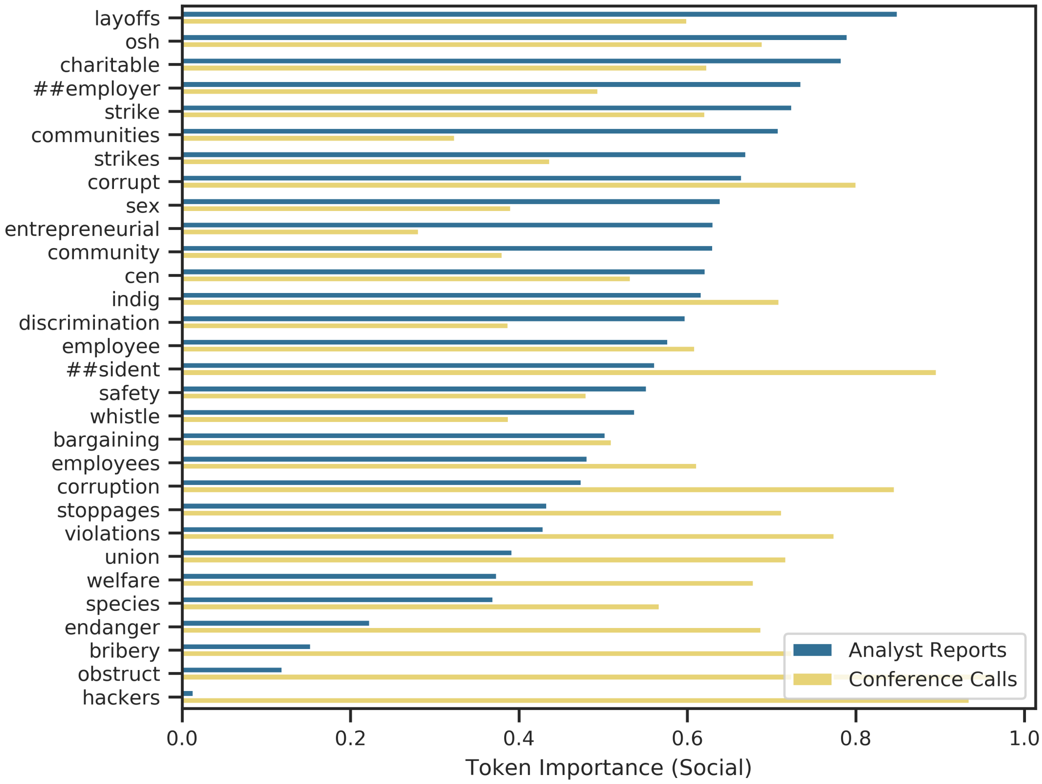


Figure IA5
Number of broker closures over time

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

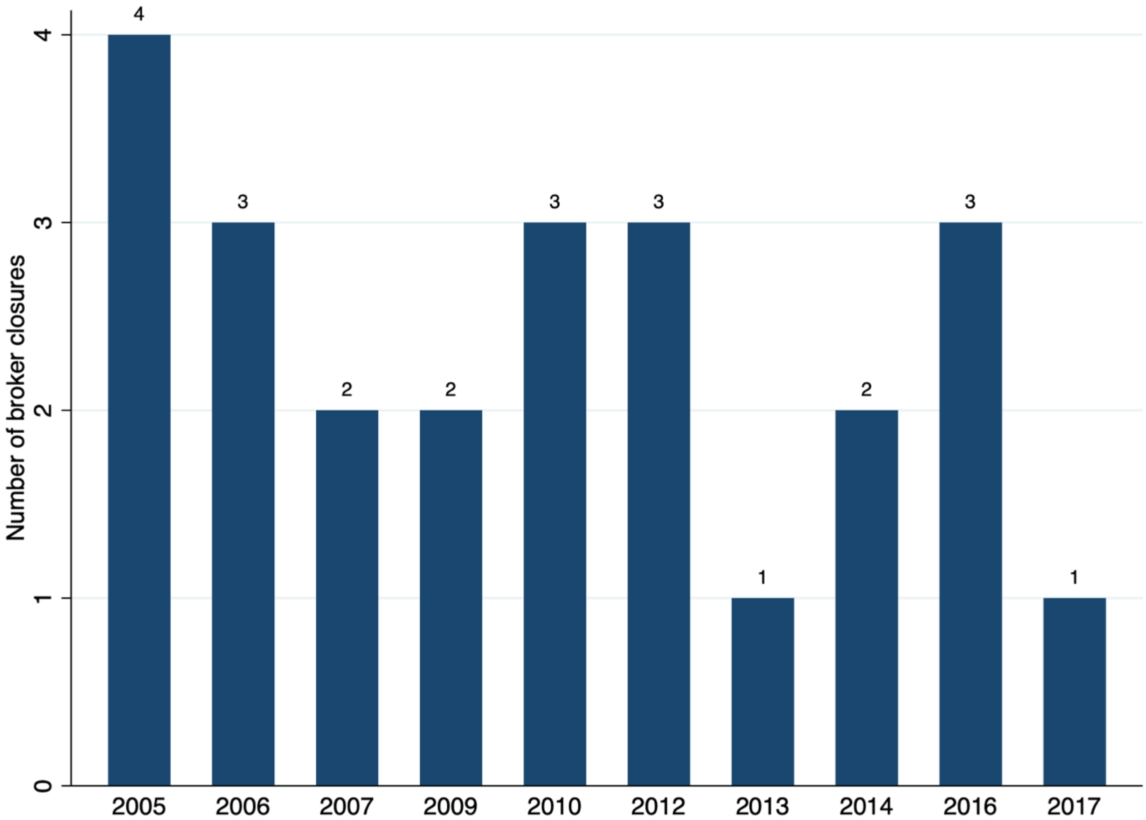


Table IA1
Queries of E&S issues

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 IA2
Important training examples in active learning

This table lists examples from two corpora 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 IA3
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 IA4
Examples of E&S-related questions during earnings conference calls

This table lists examples of E&S-related questions during earnings conference calls used in Table 6. At the call-analyst 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 Linda Ann Bolton-Weiser (Female) from Caris & Company, Inc. on the FQ1 2011 earnings conference call of Kimberly-Clark Corporation held on 04/25/2011. Listen, just kind of a big picture question about -- you've had commodity cost pressures pretty on and off for several years now, and you've been really good about finding cost savings and increasing your cost savings. And you're talking about more overhead cost reductions now. I mean, how does that affect your employees and morale? I mean, they're just constantly in a cost-cutting, cut this, cut that type of environment. Can you just kind of address that question about morale and giving them the idea that there's growth and not just cutting?
Example 2: 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.
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 Nancy Avans Bush (Female) from NAB Research, LLC on the FQ1 2019 earnings conference call of Bank of America Corporation held on 04/16/2019. Brian, this is a question about your program to lift the minimum wage from \$15 to \$20 over the next 20 months. And I can see how this is necessary, and as you said, to "get the best people in an economy that has the unemployment rates that we do right now." But can you just kind of generally flesh out what kind of productivity improvements you're seeing in the workforce and whether this \$5 raise will be paid for by productivity?
Example 5: The question was asked by Maggie Anne MacDougall (Female) from Stifel GMP Research on the FQ2 2020 earnings conference call of Boyd Group Services Inc. held on 08/12/2020. I'm going to pull on the same thread as everyone else, which I'm sure you're happy to hear. So we had a tight labor market, and it was difficult for you to get technicians heading into COVID when we were at peak sort of employment rate in the U.S. And you guys did a really good job reinvesting the U.S. tax cut into enhanced employee benefits. Now we're kind of in the opposite situation with regards to the labor market, at least at a high level. So I'm wondering if there's been any structural change to employee cost, given that the conditions in the labor market have changed significantly.

Table IA5
Robustness checks: Using other measures of female analyst coverage

This table conducts robustness checks on our main findings in Table 3 using other measures of female analyst coverage. Panel A 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 B 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 C 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 D 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 E conducts robustness checks on our main findings in Table 3 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. 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. Heteroskedasticity-consistent 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 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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.522	0.514
No. of observations	20,402	20,402	20,402

Panel B: 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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.522	0.514
No. of observations	20,402	20,402	20,402

Panel C: 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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.522	0.514
No. of observations	20,402	20,402	20,402

Panel D: 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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.523	0.514
No. of observations	20,402	20,402	20,402

Panel E: 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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.559	0.523	0.514
No. of observations	20,402	20,402	20,402

Table IA6
Robustness checks: Using alternative ESG data

This table conducts robustness checks on our main findings in Table 3 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. Heteroskedasticity-consistent 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
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 IA7
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	No. of treated firms	No. of 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 IA8
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 conference 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. Heteroskedasticity-consistent 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
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	20,402	20,402	20,402	20,402	20,402	20,402

Table IA9
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. Heteroskedasticity-consistent 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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.582	0.541	0.538
No. of observations	20,402	20,402	20,402

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
Industry × Year FE	YES	YES	YES
Adjusted R^2	0.536	0.510	0.472
No. of observations	20,402	20,402	20,402

Table IA10
Female analysts' E&S-related discussions/questions and career outcomes

This table examines the relations 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 firm-analyst-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 firm-analyst-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 conference 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. Heteroskedasticity-consistent 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: Firm-analyst-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	-0.003	-0.004	-0.007	1.543	0.514	3.175
	(0.008)	(0.007)	(0.007)	(3.296)	(2.965)	(3.036)
Ln(1 + N_E&S sentences)	-0.001			-3.459*		
	(0.002)			(1.923)		
Female × Ln(1 + N_E&S sentences)	-0.006			0.666		
	(0.007)			(4.335)		
Ln(1 + N_E sentences)		0.000			-3.979*	
		(0.003)			(2.269)	
Female × Ln(1 + N_E sentences)		-0.006			3.874	
		(0.008)			(4.624)	
Ln(1 + N_S sentences)			-0.005			-0.918
			(0.003)			(2.908)
Female × Ln(1 + N_S sentences)			0.004			-7.381
			(0.011)			(7.985)
Forecast frequency	0.006***	0.006***	0.006***	-9.142*	-9.538*	-10.728**
	(0.001)	(0.001)	(0.001)	(5.052)	(5.012)	(4.983)

Forecast horizon	0.000	0.000	0.000	0.869***	0.891***	0.921***
	(0.000)	(0.000)	(0.000)	(0.333)	(0.333)	(0.332)
# firms followed	0.003***	0.003***	0.003***	0.013	0.013	0.012
	(0.000)	(0.000)	(0.000)	(0.010)	(0.010)	(0.010)
# industries followed	0.002	0.002	0.002	-0.093	-0.094	-0.089
	(0.001)	(0.001)	(0.001)	(0.136)	(0.136)	(0.136)
General experience	0.006***	0.006***	0.006***	-0.119	-0.118	-0.130
	(0.001)	(0.001)	(0.001)	(0.559)	(0.559)	(0.559)
Constant	-0.082***	-0.083***	-0.082***	0.061	0.065	0.060
	(0.010)	(0.010)	(0.010)	(0.185)	(0.185)	(0.185)
Firm × Year FE	YES	YES	YES	YES	YES	YES
Broker × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.342	0.342	0.342	0.098	0.098	0.098
No. of observations	125,971	125,971	125,971	98,662	98,662	98,662

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

	Star analyst			Forecast accuracy		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.023***	-0.021***	-0.020***	2.161	2.006	1.929
	(0.007)	(0.007)	(0.007)	(3.034)	(2.696)	(2.954)
Ln(1 + N_E&S questions)	0.006**			3.312		
	(0.003)			(2.192)		
Female × Ln(1 + N_E&S questions)	0.012			-1.884		
	(0.008)			(5.405)		
Ln(1 + N_E questions)		0.012***			5.366	
		(0.004)			(3.988)	
Female × Ln(1 + N_S questions)		0.032			-5.156	
		(0.020)			(10.543)	
Ln(1 + N_S questions)			0.005*			2.517
			(0.003)			(2.495)
Female × Ln(1 + N_S questions)			0.004			-1.197
			(0.008)			(6.050)

Forecast frequency	0.007***	0.007***	0.007***	0.812**	0.828**	0.826**
	(0.001)	(0.001)	(0.001)	(0.389)	(0.388)	(0.389)
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***	-0.194	-0.195	-0.194
	(0.000)	(0.000)	(0.000)	(0.152)	(0.152)	(0.152)
# industries followed	-0.002	-0.002	-0.002	-0.448	-0.452	-0.450
	(0.001)	(0.001)	(0.001)	(0.596)	(0.596)	(0.596)
General experience	0.006***	0.006***	0.006***	0.279	0.286	0.283
	(0.001)	(0.001)	(0.001)	(0.187)	(0.187)	(0.187)
Constant	-0.107***	-0.107***	-0.107***	-8.176	-7.809	-7.926
	(0.011)	(0.011)	(0.011)	(5.602)	(5.578)	(5.603)
	(0.007)	(0.007)	(0.007)	(3.034)	(2.696)	(2.954)
Firm × Year FE	YES	YES	YES	YES	YES	YES
Broker × Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.444	0.444	0.444	0.080	0.080	0.080
No. of observations	92,357	92,357	92,357	78,431	78,431	78,431

Table IA11
Female analysts and corporate governance performance

This table examines the relation between female analyst coverage and corporate governance performance. Columns (1) and (2) present the results using firms' governance scores (*G score*). Columns (3)-(8) present the results using corporate governance performance sub-scores. 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. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Variable	G score (1)	G score (2)	CSR strategy (3)	CSR strategy (4)	Management (5)	Management (6)	Shareholders (7)	Shareholders (8)
N_female	0.003	-0.001	0.020***	0.002	0.006	0.000	0.007	-0.004
	(0.003)	(0.002)	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Industry × Year FE	YES		YES		YES		YES	
Firm FE		YES		YES		YES		YES
Year FE		YES		YES		YES		YES
Adjusted R^2	0.195	0.648	0.450	0.768	0.135	0.564	0.0418	0.665
No. of observations	20,402	19,990	20,402	19,990	20,402	19,990	20,402	19,990