# 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

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***Keywords***: female equity analysts; analyst monitoring; corporate environmental and social performance; natural language processing; computational linguistic methods; FinBERT; analyst reports; earnings conference calls

***JEL classification***: G24; G30; G40

[*] 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 Rui Dai, David Du, Nick Gantchev, Allen Huang, 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 Fordham 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), and the SFS Cavalcade Asia-Pacific Conference (virtual). 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.

# Female Equity Analysts and Corporate Environmental and Social Performance


## Abstract

Using a novel sample of sell-side equity analysts with gender data over the period 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. To uncover the underlying economic mechanisms, we develop machine learning models to sift through 2.4 million analyst reports and over 120,000 earnings call transcripts. We find that female equity analysts are more likely to discuss E&S issues in reports and on calls than their male counterparts. We conclude that female equity analysts play a significant monitoring role in enhancing corporate E&S performance.



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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 practices, innovation strategies, and workplace safety (Yu 2008; Irani and Oesch 2013; Chen, Harford, and Lin 2015; Guo, Pérez-Castrillo, and Toldrà-Simats 2019; Bradley, Mao, and Zhang 2022). 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 analyst monitoring, resulting in improved corporate E&S performance. Surveys in both psychology and economics (Beutel and Marini 1995; Schwartz and Rubel 2005) indicate that women relative to men tend to score higher on values related to community and compassion and score lower on materialism. Evidence further suggests that, relative to men, women have more prosocial and altruistic responses to, and preferences for, redistribution and equity

[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.

(Bertrand 2011). Relatedly, experimental and survey evidence in psychology (Silverman 2003; Castillo, Ferraro, Jordan, and Petrie 2011) shows that women, 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, managers whose firms are followed by female analysts will pay more attention and invest more in E&S policies and practices than their counterparts 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 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. This finding is robust to alternative measures of corporate E&S performance. In terms of economic significance, a one-standard-deviation increase in the number of female analysts following a firm is associated with a 3% increase in that firm's E&S score relative to the sample mean.

Employing both the change-on-change regressions and the instrumental variable approach, we establish a causal effect of female analyst coverage and corporate E&S performance. We find that the initiation of a firm's female analyst coverage is followed by a significant improvement in that firm's E&S performance. Likewise, we find that losing a firm's female analyst coverage leads to a significant drop in that firm's E&S performance. This set of results suggests that reverse causality is unlikely to drive our main findings. Following Yu (2008), we use the expected analyst coverage resulting from changes in broker size as an instrument for the number of female analysts following a firm. The two-stage least squares regression indicates that the instrumented number of female analysts is positively and significantly associated with that firm's E&S score, suggesting that the effect of female analyst coverage on firm-level E&S performance is likely to be causal.

In terms of the underlying economic mechanisms, we 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 on earnings conference calls than their male counterparts. To capture those discussions, 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 method is likely to be ineffective. Based on the FinBERT model (Huang, Wang, and Yang 2022), a state-of-the-art large language model trained on financial text, 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 E&S issues. We show that female analysts' reports contain more discussion about E&S issues than male analysts' reports. Similarly, we show that female analysts are more likely to raise E&S-related questions on conference calls than male analysts.

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 association is stronger in firms followed by female analysts with more general and/or firm-specific experience than in their counterparts followed by female analysts with less general or firm-specific experience. We further show that there is no complementarity between female directors/executives and female analysts in enhancing corporate E&S performance, suggesting that female analysts have a unique role in enhancing firms' E&S practices.

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; Masta and Miller 2013; Levi, Li, and Zhang 2014; Tate and Yang 2015; Hsu, Li, and Pan 2022). 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 disclosure, corporate governance, innovation strategies, and workplace safety. Bridging these two literatures, we show that female equity analyst coverage of a firm is positively and significantly associated with that firm's E&S performance.

Second, we contribute to the literature on big data and computational linguistic methods in finance and accounting (see some recent developments in measuring corporate environmental performance by Kölbel, Leippold, Rillaerts, and Wang 2022; Li, Shan, Tang, and Yao 2022; Sautner, Vilkov, van Lent, and Zhang 2022). We fine-tune FinBERT, a pre-trained language model using financial text introduced by Huang, Wang, and Yang (2022), on E&S classification tasks with active learning. We apply the fine-tuned models to much larger corpora than previously studied (over 2.4 million analyst reports and over 120,000 call transcripts; compared to 50,000 10-K filings in Kölbel et al. (2022) and 140,000 earnings calls in Li et al. (2022)). Our results demonstrate that the use of active learning in a large language model is an effective way to classify domain-specific text. In particular, many tasks, including identifying E&S-related discussions, are often hindered by the limited availability of in-domain training data, which is employed to account for specialized language and terminology within a context. By applying active learning to curate domain-specific labeled examples, we present a novel approach for effectively fine-tuning large language models for specialized tasks.

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 2022), we show that female equity analysts play a significant monitoring role in helping to enhance corporate E&S performance.

## 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 (2022) show a positive association between board gender diversity and corporate environmental performance using firm- and facility-level measures.

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 the level 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. 2022).[2] The advantage of these methods is that they identify domain-specific keywords without requiring extensive

[2] 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.

human input. The third and relatively new approach is using a machine learning model to classify if sentences are relevant to E&S issues. 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 (2022) 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 features.

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 higher ESG firms significantly more than short-term investors do. Dyck et al. (2022) 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 in earnings conference calls and corporate site visits; and 2) they disseminate their research insights to institutional and retail investors via research reports and business media interviews. Prior work shows that equity analysts help improve corporate governance and workplace practices (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.[3]

[3] 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.

Evidence 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.

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).[4] 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.

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

[4] Because of the long-term nature of E&S investments, institutional investors with long horizons play a critical role in promoting E&S policies and practices (Chen, Dong, and Lin 2020; Starks, Venkat, and Zhu 2020; Flammer 2021). For example, Blackrock states in its stewardship reports that the asset management firm's engagement with portfolio firms is to convey its thinking on long-term value creation (Azar, Duro, Kadach, and Ormazabal 2021).

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 the firms they follow. Analysts could potentially use these opportunities to express concerns about these firms.[5] Given gender differences in values related to community and compassion, we expect female analysts have a stronger intrinsic motivation than their male counterparts to pay attention to E&S issues. 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.

[5] 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 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 on calls 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 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

### *3.1. Why FinBERT?*

To capture analyst monitoring through their research activities, we employ 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 2022), 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.[6] 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 (2022) show that the fine-tuning step requires only a relatively small training sample to achieve a high text classification accuracy.

In this paper, we fine-tune FinBERT to classify if sentences in the analyst reports or questions on 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 (2022) 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' Corporate Social Responsibility (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

[6] 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.

expressions used by analysts during Q&A sessions of earnings calls. To address this challenge, we propose fine-tuning the original FinBERT model using domain-specific training examples from analyst reports and earnings calls, which will help improve the model's ability to detect E&S-related discussions in these domains.

*3.2. Constructing domain-specific training examples via active learning*

We employ *active learning*, a human-in-the-loop machine learning approach, to find domain-specific training examples and subsequently train two different E&S classification models, one for analyst reports and the other for conference calls. In active learning, a classification model is improved iteratively.

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 generate a set of initial training examples. Passages containing those keywords are tentatively labeled as positive examples (E or S), and random passages are used as negative examples (Non-E&S). In Step 2, we use the initial training sample to fine-tune the FinBERT model into a *Noisy E&S model*. In Step 3, we use the Noisy model to classify the initial training sample. Given the Noisy model's outputs, a subset of important examples is labeled by human annotators (Cormack and Grossman 2014). 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 (2022) 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). In a nutshell, 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 (on conference calls). Table IA2 in the Internet Appendix provides examples of E&S-related sentences in analyst reports. Table IA3 in the Internet Appendix provides examples of E&S-related questions on earnings conference calls.

### *3.3. Capturing E&S-related discussions*

We employ the fine-tuned FinBERT models to classify each sentence (question) in analyst reports (conference calls). 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 on 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 environmental issues in their reports, they tend to raise more social-related questions on calls.[7] In terms of industry breakdown, it is not surprising that discussions of environmental issues are heavily concentrated in resource-intensive industries that tend to have larger environmental footprints, such as Utilities, Chemicals, Energy, 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.[8] 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 for each corpus, which provides a corpus-specific measure of the importance of each token in the texts.

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.,

[7] 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 on conference calls. Second, conference calls and analyst reports play distinctly different roles in shaping a firm's information environment, whereby the former provides a platform for analysts to question (unobserved) 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 on calls. Consistent with the above argument, Figure IA3 in the Internet Appendix shows different E&S issues discussed in reports versus those raised on calls.

[8] 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.

*pollution, renewables, climate, greenhouse*) are more important on 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 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 on 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).[9] We use the proprietary-weighted aggregate scores that Refinitiv provides to investors (i.e., z-scores). These rank-based scores range from 0 to 1 and measure the E&S performance relative to all other firms in the same industry group in a given year.

Our Refinitiv data set was downloaded in April 2022 from WRDS. Our sample period starts in 2005 because the coverage of Capital IQ, which will help us determine analyst

[9] 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; and 3) it is used by prior work, see, for example, Dyck et al. (2019), and hence it is easier for us to benchmark with prior work. We are aware of some controversies associated with the Refinitiv ESG database (Berg, Koelbel, and Rigobon 2022), as well as some inconsistencies across various ESG databases. For robustness checks, we also employ three other ESG databases: Thomson Reuters's ASSET4 (discontinued after 2019), MSCI's KLD Stats, and Morningstar's Sustainalytics.

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). We obtain firm financials from Compustat, board characteristics from BoardEx, executive characteristics from ExecuComp, and institutional ownership from WRDS Thomson Reuters Stock Ownership. 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).[10]

*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.[11] 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

[10] 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. As a result, for firm-year observations in I/B/E/S for which we could not find analyst gender data, we assume zero analyst coverage (even though I/B/E/S suggests otherwise).
[11] 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.

gender data for 6,644 analysts, representing 70% of the analysts affiliated with the 292 brokers in our analyst report sample.

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 on earnings conference calls*

We download 64,075 earnings call transcripts covering 2,186 firms over the period 2007–2020 from Capital IQ.[12] 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

[12] 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 have earning conference calls.

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 following, and the average female ratio of analysts is 7.3%.[13] 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).[14]

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, and a positive association between the total number of analysts (*N_analysts)* and three different measures of corporate E&S performance. Examination of the correlation matrix suggests that multicollinearity is unlikely to be an issue. Given that omitted variable bias in univariate correlations can mask the true relations between the variables, we next employ multiple regressions to examine the factors associated with corporate E&S performance.

## 5. Main Results

### *5.1. Female equity analysts and corporate E&S performance*

[13] In unreported analysis, we find that there is no time trend in either the number of female analysts, or of analysts overall, following our sample firms over the sample period 2004‒2020.

[14] There are a number of reasons for the mean/median number of analysts following our sample firms to be lower than that reported in Yu (2008) and Chen, Harford, and Lin (2015). First, both Yu (2008) and Chen, Harford, and Lin (2015) use the I/B/E/S Summary file to obtain the number of analysts following these firms (*N_analysts*) based on the understanding that these analysts contribute to the consensus forecast in a year. In contrast, to identify analyst gender, our analyst sample is from the I/B/E/S Detail Recommendations file, which provides analysts' last names and first-name initials. We note that over a third of analysts make earnings forecasts but never make stock recommendations. Second, our sample size of 3,567 firms is much larger than those used in prior work for which we do not require sample firms to have analyst coverage. For example, Chen, Harford, and Lin (2015) employ a sample of 1,179 firms over the period 1999‒2011. Third, we only count analysts with identified gender information (from the Capital IQ Professionals). As a result, we will miss analysts in the I/B/E/S Detail Recommendation file for whom we could not determine broker names, analyst full names, or analyst gender. To mitigate the problem of missing (unidentified) analysts, as a robustness check, we use the female analyst ratio 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 IA4 in the Internet Appendix).

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

$$E/S\ score_{i,t+1} = \alpha + \beta_1\ N\_female_{i,t} + \beta_2 Firm\ characteristics_{i,t} + Ind/Firm\ FE + Year\ FE + \epsilon_{it}, \tag{1}$$

where the dependent variable is the E&S score, E score, or S score of firm $i$ in year $t$. 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 (firm) fixed effects (FEs) to control for time-invariant industry (firm) unobservables that might drive both female analyst coverage and corporate E&S performance. We include year fixed effects to control for time trends in corporate CSR investments and/or time trends in female equity analysts following. Table 3 presents the regression results.

Columns (1), (3), and (5) of Panel A present the regression results with different dependent variables capturing E&S performance (*E&S score*), environmental performance (*E score*), and social performance (*S score*) and industry and year fixed effects. Because our panel data set includes small firms with short time series, including industry and year fixed effects is our preferred specification (Gormley and Matsa 2014). 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 and *E&S score*.[15] 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

[15] As a robustness check, we use the number of analysts following *(N_analysts)* instead of the natural logarithm of one plus the number of analysts following. Table IA5 in the Internet Appendix shows our main findings remain.

(SG&A) (Di Giuli and Kostovetsky 2014; Chen, Dong, and Lin 2020). 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, a one-standard-deviation increase in *N_female* (0.856) is associated with a 0.013 (0.856 × 0.015) increase in *E&S score* (ranging from 0 to 1), which is equivalent to a 3.1% (0.013/0.420) 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 and year FEs as an example (column (1)), we find that the economic significance of (i.e., the change in E&S score driven by a one-standard-deviation increase in) *N_female* is higher than that for *Ln(1+N_analysts), 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*.

To address the potential endogeneity concerns, columns (2), (4), and (6) of Panel A present the regression results controlling for firm and year fixed effects. We show that there remains a positive and significant association between *N_female* and *E&S score*. In contrast, the negative association between *Ln(1+N_analysts*) 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 on the analyst coverage variable.[16] Some of the firm-level controls exhibit the same association after including firm and year fixed effects, with the following exceptions. *Tobin's Q*, *ROA*, and *Leverage* lose their significant associations with any of the E&S performance measures. *Institutional ownership* is positively and significantly associated with *E&S score* (and *S score*) controlling for firm and year fixed effects, whereas it is negatively and significantly associated with corporate E&S performance controlling for industry and year fixed effects. The inconsistencies with Dyck et al. (2019) are probably due to sample selection—they use an international sample that excludes U.S. firms.

*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.

*5.2. The change-on-change regressions*

To assess whether the identified association between the number of female analysts following a firm and that firm's E&S performance is likely to be causal, we exploit the temporal variation in our data.

The firm fixed-effects model in Table 3 Panel A is not perfect due to the slow-moving nature of our key variable of interest, namely, the number of female analysts following; about three-quarters of the firm-year observations do not experience any change in the number of female analysts following compared with the previous year. For a more definitive model, we

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[16] Driskill, Kirk, and Tucker (2020) point out that firm fixed effects also complicate the interpretation of sticky control variables.

employ a change-on-change regression specification, which helps maximize the temporal variation in the variable of interest, while removing time-invariant firm-level unobservables with an approach similar to the firm fixed-effects model (Griffin, Li, and Xu 2021):

$$\Delta_{t\to t+1} E\&S\ score_i = \alpha + \beta_1\, \Delta_{t-2\to t-1} N\_female_i + \beta_2 \Delta_{t-2\to t-1} Firm\ characteristics_i + Ind\ FE + Year\ FE + \varepsilon_{it}. \qquad (2)$$

To account for the possibility that it might take time for female equity analysts to have an effect on corporate E&S performance, we employ as the dependent variable: the changes in E&S performance following a change in female analyst coverage in one, two, and three years, respectively.

We run two separate regressions. In the first regression, we compare firm-year observations for which there has been a drop in the number of female equity analysts following from at least one to zero, and the control group is a sample of firm-year observations for which there has been at least one female analyst providing coverage throughout. In the second regression, we compare firm-year observations for which there has been an increase in the number of female equity analysts following from zero to at least one, and the control group is a sample of firm-year observations for which there has been no female analyst following throughout. Table 4 Panel A provides an overview of samples used in those two regressions.

Panel B presents the results for the first regression. We show that a drop in female equity analyst coverage is associated with a significant drop in E&S performance compared to peer firms with unchanged female equity analyst coverage. Panel C presents the results for the second regression. We show that an increase in female equity analyst coverage is associated with a significant increase in E&S performance, driven mainly by E performance but not S performance.

Overall, the change-on-change regressions provide suggestive evidence that there is a causal effect of female analysts following a firm on that firm's E&S performance. Moreover, female analysts are more likely to initiate changes in environmental issues rather than social issues, suggesting that social policies and practices are more difficult to implement and/or take a longer time to show effects, whereas environmental policies/practices are less controversial than social ones.

### *5.3. The instrumental variable approach*

We also employ the instrumental variable approach to extract the exogenous component of female analyst coverage following Yu (2008). Specifically, the size of a brokerage house changes over time, usually depending on the change in its revenue or profit, and is not affected by the E&S performance of firms that the brokerage house covers. When a brokerage house reduces its size, it employs fewer female analysts. The idea of the instrument is that the change of female analyst coverage driven by the change of brokerage size is exogenous to the outcome variable – corporate E&S performance.[17]

Following Yu (2008), we construct the instrumental variable as follows:[18]

$$ExpCoverage_{i,j,t} = (Brokersize_{j,t} / Brokersize_{j,0}) \times Coverage_{i,j,0} \quad (3)$$

$$ExpCoverage_{i,t} = \sum_{j=1}^{n} ExpCoverage_{i,j,t} \quad (4)$$

where $ExpCoverage_{i,j,t}$ is the expected analyst coverage of firm *i* from brokerage *j* in year *t*. $Brokersize_{j,t}$ and $Brokersize_{j,0}$ are the number of analysts employed by brokerage *j* in year

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[17] One may argue that a brokerage's decision to cover (or drop) a firm is not random. It is worth noting that a selection that affects actual coverage has no effect on expected coverage (our IV), because expected coverage measures a brokerage's tendency to keep its coverage of a firm due to the former's size expansion, which has no bearing on the actual decision of whether to cover a firm or not. Another concern is that, whereas Yu (2008) uses expected coverage to instrument the number of analysts following a firm, we use expected coverage to instrument the number of female analysts following that firm. Our assumption is that in general, female analyst coverage is proportionate to total analyst coverage. The F-test in the first-stage regression suggests that our IV is not weak.

[18] The instrument has been used in other recent studies, including He and Tian (2013) and Guo, Pérez-Castrillo, and Toldrà-Simats (2019).

$t$ and in the benchmark year $0$, respectively. We use the year 2004 as the benchmark year because it is the starting year of our sample. $Coverage_{i,j,0}$ is the number of analysts from brokerage $j$ following firm $i$ in year $0$. We limit the maximum of $ExpCoverage_{i,j,t}$, the expected number of analysts that a brokerage assigns to cover a firm, to one, since in practice brokerage houses rarely assign more than one analyst to cover a firm. Hence, $ExpCoverage_{i,j,t}$ ranges from 0 to 1, measuring the probability of a brokerage continuing to cover firm $i$ in year $t$ based on the brokerage size in that year compared to the initial year. The instrumental variable $ExpCoverage_{i,t}$ is the expected number of analysts from all brokerage houses covering firm $i$ in year $t$.[19]

We use $ExpCoverage_{i,t}$ to instrument *N_female* and estimate the following two-stage least squares (2SLS) regressions:

$$N\_female_{i,t} = \alpha + \beta ExpCoverage_{i,t} + \gamma X_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{it}, \quad (5a)$$

$$E\&S\ score_{i,t} = \alpha + \beta \widehat{N\_female}_{i,t} + \gamma X_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{it}. \quad (5b)$$

Equation (5a) represents the first-stage regression where we instrument for the number of female analysts covering firm $i$ in year $t$ using that firm's expected coverage in year $t$. Equation (5b) is the second-stage regression where we regress *E&S score* on the expected number of female analysts estimated from the first stage. We include firm and year fixed effects in both stages of regressions.

Table 5 presents the results. The first stage regression result in column (1) indicates that *ExpCoverage* is significantly correlated with *N_female*. The F-statistic (38.41) is greater than 10 (which is the critical value following Stock and Watson (2019)). Both suggest that our instrument variable does not suffer from the weak instrument problem. The results from

[19] Following Yu (2008), we drop all observations in the benchmark year (2004) since expected coverage for that year is one by construction. See Yu (2008) Table 6 for an example of how we compute the expected coverage, $ExpCoverage_{i,t}$.

the second stage regressions in columns (2)-(4) show that the coefficient on the instrumented *N_female* is positive and significant, and of greater magnitude than those in the panel data regressions (Table 3). Overall, the instrumental variable analysis suggests that the effect of female analyst coverage on firm-level 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 on earnings conference calls.

### *6.1. Analyst reports*

Table 6 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 times 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.

To address the concern that broker culture could be behind our findings, we include broker times year fixed effects, controlling for a time-varying broker culture that might 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%, a 4.7% (1.4%/29.6%) increase.

*6.2. Earnings conference calls*

Table 7 Panel A presents the summary statistics at the call-analyst level. We show that 15.3% of 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%, a 7% (1.0%/15.3%) increase.

## 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.[20] *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. *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 the Institutional Investor All-Star status in a given year, and zero otherwise. Table 8 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

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

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 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 9 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. Interestingly, we show that the coefficient on the interaction term *N_female* × *N_female directors* is not significantly different from zero, suggesting that there is no complementarity between female directors and female analysts in enhancing corporate E&S performance.

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 there is no complementarity between female executives and female analysts in enhancing corporate E&S performance.

In summary, the results in Table 9 help support our hypothesis that female analysts play a unique role in monitoring firms' E&S practices.[21]

### *7.3. Using alternative ESG data sets*

Given the controversies and/or inconsistencies associated with various ESG databases (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 databases to measure E&S performance. We employ data from three different ESG rating providers: Thomson Reuters' ASSET4,[22] MSCI's KLD Stats,[23] and Morningstar's Sustainalytics. 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). 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.

### *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 IA7 presents the results examining the relation between female analyst coverage and

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[21] In untabulated analysis, we include *N_female, N_female directors,* and *N_female executives* in one regression specification. We find that female directors have the largest effect on corporate E&S performance, while female executives lose significance.
[22] In 2018, Refinitiv acquired ASSET4 from Thomson Reuters and renamed and replaced it with Refinitiv's ESG ratings.
[23] In 2009, KLD, formerly known as Kinder, Lydenberg, Domini & Co., was acquired by RiskMetrics. In 2010, MSCI acquired RiskMetrics and renamed the legacy database KLD as MSCI's KLD Stats.

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 when including industry and 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 when 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.

In summary, the results in Table IA7 help support our main hypothesis that gender differences in values and willingness to delay gratification are essential elements of the monitoring role of female equity analysts in corporate E&S performance.

*7.5. Controlling for Top5 institutional ownership*

To examine whether the positive association between female analyst coverage of a firm and that firm's E&S performance captures the possibility that these female analysts are simply voicing the concerns of their clients with long-term investment horizons and E&S preferences, we repeat our analysis in Equation (1), including *Top5 institutional ownership*. Table IA8 presents the results. We show that our main findings remain, suggesting that female analysts play a distinct role in monitoring firms' E&S practices.

*7.6. 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 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 analyst status and forecast accuracy. Our analysis is at the firm-analyst-year level.

*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. In order 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 6 and 7. We then apply the logarithmic transformation to get the intensity measures, *Ln(1 + N_E&S sentences)* and *Ln(1 + N_E&S questions)*.

Table IA9 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.

*7.7. Subsample analysis: The Paris Agreement*

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

2021.[24] Table IA10 presents the results. We find the positive and significant association between female analysts and corporate E&S performance in both sub-periods.

## 8. Conclusions

Using a novel sample of 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. Additional analyses using the change-on-change regressions and the instrumental variable approach suggest that the effect of female analyst coverage on firms' E&S performance is likely to be causal.

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 on calls than their male counterparts.

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

[24] The daily climate change index over the period 1984–2017 shown in Engle, Giglio, Kelly, Lee, and Stroebel (2020, Figure 2) indicates the Paris Agreement corresponds to the third highest spike in terms of media attention to the climate change risk.

**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. |
| 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_analysts | The number of analysts covering a firm in a given year. |
| Ln(1 + N_analysts) | 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. |
| D1_E&S score | Change of the E&S score from year $t$ to $t+1$. Other change variables in E score and S score are defined analogously. |
| D2_E&S score | Change of the E&S score from year $t$ to $t+2$. Other change variables in E score and S score are defined analogously. |
| D3_E&S score | Change of the E&S score from year $t$ to $t+3$. Other change variables in E score and S score are defined analogously. |
| ExpCoverage | The expected number of analysts from all brokers covering firm $i$ in year $t$. The expected coverage from broker $j$ is the product of analyst coverage from broker $j$ for firm $i$ in the year 2004 (i.e., the first year of our sample period) and the ratio of broker $j$’s size in year $t$ to broker $j$’s size in the year 2004. |
| 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. |
| 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. |
| Top5 institutional ownership | The fraction of shares outstanding held by the five largest institutional investors. |
| **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. |
| N_E&S sentences | The count of E&S-related sentences in an analyst report. |
| Ln(1 + N_E&S sentences) | Natural logarithm of one plus the count of E&S-related sentences in an analyst report. |
| N_E sentences | The count of environmental-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. |
| N_S sentences | The count of social-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. |
| N_E&S questions | The count of E&S-related questions by an analyst during a firm's earnings conference call. |
| 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. |
| N_E questions | The count of environmental-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. |

| | |
|---|---|
| N_S questions | The count of social-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. |
| Brokerage size | Number of analysts making at least one forecast at the focal brokerage in a given year. |
| Ln(Brokerage size) | Natural logarithm of the brokerage size in a brokerage-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 | $5^{th}$ Percentile | Median | $95^{th}$ Percentile | SD |
|---|---|---|---|---|---|
| E&S score | 0.420 | 0.098 | 0.325 | 0.918 | 0.287 |
| E score | 0.412 | 0.098 | 0.281 | 0.937 | 0.312 |
| S score | 0.427 | 0.077 | 0.355 | 0.922 | 0.291 |
| 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 |
| N_analysts | 4.385 | 0.000 | 3.000 | 14.000 | 4.814 |
| Ln(1 + N_analysts) | 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 | Ln(1+N_ analysts) | 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 | | | | | | | | | | | |
| Ln(1 + N_analysts) | 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. 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

| | E&S score | E&S score | E score | E score | S score | S score |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| N_female | 0.015*** | 0.004** | 0.019*** | 0.005** | 0.011*** | 0.003 |
| | (0.004) | (0.002) | (0.004) | (0.002) | (0.004) | (0.002) |
| Ln(1 + N_analysts) | -0.010** | -0.006* | -0.011** | -0.008* | -0.009* | -0.004 |
| | (0.005) | (0.003) | (0.005) | (0.004) | (0.005) | (0.004) |
| Firm size | 0.126*** | 0.052*** | 0.129*** | 0.050*** | 0.123*** | 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 | 0.011*** | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| ROA | 0.058*** | 0.012 | 0.024 | 0.008 | 0.093*** | 0.015 |
| | (0.018) | (0.018) | (0.019) | (0.021) | (0.018) | (0.019) |
| Leverage | -0.071*** | -0.022 | -0.068*** | -0.017 | -0.074*** | -0.027 |
| | (0.016) | (0.017) | (0.018) | (0.020) | (0.017) | (0.018) |
| SG&A | 0.128*** | 0.050*** | 0.128*** | 0.042* | 0.127*** | 0.058*** |
| | (0.018) | (0.018) | (0.020) | (0.021) | (0.019) | (0.019) |
| Cash holdings | -0.064*** | -0.015* | -0.051*** | -0.016 | -0.077*** | -0.014 |
| | (0.012) | (0.008) | (0.013) | (0.010) | (0.012) | (0.009) |
| Tangibility | -0.014 | -0.058*** | 0.004 | -0.046*** | -0.033** | -0.070*** |
| | (0.015) | (0.014) | (0.016) | (0.016) | (0.016) | (0.015) |
| Board independence | 0.010 | 0.038 | -0.001 | 0.006 | 0.021 | 0.070** |
| | (0.032) | (0.026) | (0.035) | (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 | -0.025** | 0.030*** | -0.040*** | 0.003 | -0.009 | 0.058*** |
| | (0.012) | (0.012) | (0.013) | (0.014) | (0.012) | (0.013) |
| Constant | -0.610*** | -0.025 | -0.628*** | 0.024 | -0.592*** | -0.075 |
| | (0.034) | (0.049) | (0.038) | (0.059) | (0.034) | (0.051) |
| FF48 FE | YES | | YES | | YES | |
| Firm FE | | YES | | YES | | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| Adjusted $R^2$ | 0.553 | 0.833 | 0.517 | 0.806 | 0.507 | 0.793 |
| No. of observations | 20,423 | 19,990 | 20,423 | 19,990 | 20,423 | 19,990 |

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

| | Emissions reduction | Innovation | Resource use |
|---|---|---|---|
| Variable | (1) | (2) | (3) |
| N_female | 0.020*** | 0.013*** | 0.018*** |
| | (0.004) | (0.005) | (0.004) |
| Ln(1 + N_analysts) | -0.017*** | -0.000 | -0.013** |
| | (0.006) | (0.005) | (0.006) |

| | | | |
|---|---|---|---|
| Firm size | 0.131*** | 0.073*** | 0.136*** |
| | (0.003) | (0.004) | (0.003) |
| Tobin's Q | 0.012*** | 0.008*** | 0.010*** |
| | (0.002) | (0.002) | (0.003) |
| ROA | 0.007 | -0.040** | 0.029 |
| | (0.021) | (0.019) | (0.021) |
| Leverage | -0.072*** | -0.067*** | -0.080*** |
| | (0.019) | (0.018) | (0.020) |
| SG&A | 0.129*** | 0.066*** | 0.160*** |
| | (0.021) | (0.020) | (0.022) |
| Cash holdings | -0.042*** | -0.023* | -0.058*** |
| | (0.014) | (0.012) | (0.014) |
| Tangibility | 0.019 | -0.021 | -0.021 |
| | (0.018) | (0.016) | (0.018) |
| Board independence | -0.053 | 0.016 | -0.061 |
| | (0.038) | (0.037) | (0.037) |
| CEO duality | -0.008 | -0.008 | -0.011 |
| | (0.007) | (0.007) | (0.007) |
| Institutional ownership | -0.037*** | -0.051*** | -0.025* |
| | (0.014) | (0.014) | (0.014) |
| Constant | -0.763*** | -0.410*** | -0.780*** |
| | (0.041) | (0.045) | (0.040) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.463 | 0.322 | 0.482 |
| No. of observations | 20,423 | 20,423 | 20,423 |

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

| | Community | Human rights | Product responsibility | Workforce |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| N_female | 0.002 | 0.020*** | 0.008* | 0.008** |
| | (0.003) | (0.005) | (0.004) | (0.004) |
| Ln(1 + N_analysts) | 0.008** | -0.019*** | 0.002 | -0.006 |
| | (0.004) | (0.005) | (0.005) | (0.005) |
| Firm size | 0.084*** | 0.096*** | 0.065*** | 0.105*** |
| | (0.002) | (0.004) | (0.003) | (0.003) |
| Tobin's Q | 0.009*** | 0.007*** | 0.009*** | 0.021*** |
| | (0.002) | (0.003) | (0.003) | (0.002) |
| ROA | 0.006 | 0.095*** | 0.018 | -0.031 |
| | (0.019) | (0.021) | (0.024) | (0.021) |
| Leverage | -0.036** | -0.049** | -0.055*** | -0.068*** |
| | (0.015) | (0.020) | (0.020) | (0.017) |
| SG&A | 0.118*** | 0.123*** | 0.064*** | 0.078*** |
| | (0.017) | (0.020) | (0.023) | (0.020) |
| Cash holdings | -0.043*** | -0.034*** | -0.037*** | -0.003 |
| | (0.011) | (0.013) | (0.014) | (0.013) |
| Tangibility | -0.018 | -0.055*** | -0.035* | -0.002 |
| | (0.014) | (0.016) | (0.019) | (0.016) |
| Board independence | 0.066** | 0.005 | 0.057 | 0.016 |
| | (0.027) | (0.035) | (0.037) | (0.032) |
| CEO duality | 0.006 | -0.010 | 0.000 | -0.009 |

| | | | | |
|---|---|---|---|---|
| | (0.006) | (0.007) | (0.008) | (0.006) |
| Institutional ownership | 0.040*** | 0.018 | 0.007 | -0.001 |
| | (0.012) | (0.014) | (0.014) | (0.013) |
| Constant | -0.192*** | -0.602*** | -0.201*** | -0.484*** |
| | (0.030) | (0.041) | (0.041) | (0.035) |
| FF48 FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Adjusted $R^2$ | 0.328 | 0.362 | 0.216 | 0.362 |
| No. of observations | 20,423 | 20,423 | 20,423 | 20,423 |

**Table 4**
**Female analysts and corporate E&S performance: Change-on-change regressions**

This table examines the dynamic effect of female analyst coverage on firms' E&S performance using change-on-change regressions. Panel A presents the sample distribution of four types of changes in female analyst coverage. The first type refers to firms that change from having at least one female analyst in year *t-2* to having no female analyst in year *t-1*. The second type refers to firms that have at least one female analyst in both year *t-2* and *t-1*. The third type refers to firms that have zero female analyst in year *t-2* and have at least one female analyst in year *t-1*. The fourth type refers to firms that have zero female analysts in both year *t-2* and *t-1*. The dependent variables are changes of firms' E&S performance from year *t* to year *t+1* (D1), from year *t* to year *t+2* (D2), from year *t* to year *t+3* (D3). Panel B examines the change from having female analysts to having no female analyst on future changes of firms' E&S performance relative to a subsample of firms with female analyst coverage and experiencing no change in coverage. Panel C examines the change from having no female analyst to having female analysts on future changes of firms' E&S performance relative to a subsample of firms with no female analyst coverage and experiencing no change in coverage. Other control variables are the same as those in Table 3, measured as changes from year *t-2* to *t-1*, and are omitted for brevity. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in the Appendix. 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: Sample distribution of four types of changes in female analyst coverage

| Subsamples | N |
|---|---|
| LD1_Female analyst indicator switch from 1 to 0 | 1,047 |
| LD1_Female analyst indicator stays 1 | 2,361 |
| LD1_Female analyst indicator switch from 0 to 1 | 1,022 |
| LD1_Female analyst indicator stays 0 | 4,484 |

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

| | E&S score | | | E score | | | S score | | |
|---|---|---|---|---|---|---|---|---|---|
| | D1 | D2 | D3 | D1 | D2 | D3 | D1 | D2 | D3 |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| LD1_Female analyst indicator switch from 1 to 0 | -0.003* | -0.006*** | -0.007*** | -0.003* | -0.006*** | -0.007*** | -0.002 | -0.007*** | -0.006** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.003) |
| LD1_Ln(1 + N_analysts) | 0.008* | 0.009* | 0.001 | 0.011** | 0.018*** | 0.009 | 0.004 | -0.001 | -0.008 |
| | (0.004) | (0.005) | (0.007) | (0.005) | (0.006) | (0.008) | (0.005) | (0.006) | (0.008) |
| Other controls | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 0.026*** | 0.052*** | 0.076*** | 0.027*** | 0.057*** | 0.083*** | 0.024*** | 0.047*** | 0.068*** |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.003) | (0.004) | (0.002) | (0.003) | (0.004) |
| FF48 FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Adjusted $R^2$ | 0.055 | 0.083 | 0.103 | 0.033 | 0.053 | 0.067 | 0.044 | 0.083 | 0.110 |
| No. of observations | 3,408 | 3,408 | 3,408 | 3,408 | 3,408 | 3,408 | 3,408 | 3,408 | 3,408 |

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

| | E&S score | | | E score | | | S score | | |
|---|---|---|---|---|---|---|---|---|---|
| | D1 | D2 | D3 | D1 | D2 | D3 | D1 | D2 | D3 |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| LD1_Female analyst indicator switch from 0 to 1 | 0.007** | 0.008** | 0.008* | 0.009*** | 0.011*** | 0.013** | 0.004 | 0.004 | 0.003 |
| | (0.003) | (0.004) | (0.005) | (0.003) | (0.004) | (0.005) | (0.003) | (0.004) | (0.005) |
| LD1_Ln(1 + N_analysts) | -0.001 | -0.002 | 0.002 | -0.005 | -0.007 | -0.005 | 0.002 | 0.001 | 0.008 |
| | (0.003) | (0.004) | (0.005) | (0.004) | (0.005) | (0.006) | (0.003) | (0.005) | (0.005) |
| Other controls | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 0.031*** | 0.060*** | 0.094*** | 0.030*** | 0.060*** | 0.094*** | 0.032*** | 0.061*** | 0.094*** |
| | (0.001) | (0.002) | (0.003) | (0.002) | (0.003) | (0.004) | (0.002) | (0.003) | (0.004) |
| FF48 FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Adjusted $R^2$ | 0.063 | 0.086 | 0.091 | 0.040 | 0.057 | 0.065 | 0.054 | 0.083 | 0.092 |
| No. of observations | 5,506 | 5,506 | 5,506 | 5,506 | 5,506 | 5,506 | 5,506 | 5,506 | 5,506 |

**Table 5**
**Female analysts and corporate E&S performance: An instrumental variable approach**

This table examines the relation between female analyst coverage and firms' E&S performance using an instrumental variable approach. Following Yu (2008), we use the expected analyst coverage (*ExpCoverage*) as an instrument for the number of female analysts in the 2SLS regressions. Column (1) presents the result from the first-stage regression. Columns (2)-(4) present the results from the second-stage regressions where the dependent variables are *E&S score*, *E score*, and *S score*, respectively. 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 | N_female<br>(1) | E&S score<br>(2) | E score<br>(3) | S score<br>(4) |
|---|---|---|---|---|
| ExpCoverage | 0.068*** | | | |
| | (0.015) | | | |
| N_female | | 0.114*** | 0.146*** | 0.082* |
| | | (0.043) | (0.055) | (0.042) |
| Ln(1 + N_analysts) | 0.850*** | -0.116*** | -0.144*** | -0.087** |
| | (0.052) | (0.042) | (0.053) | (0.041) |
| Firm size | 0.009 | 0.063*** | 0.064*** | 0.061*** |
| | (0.063) | (0.011) | (0.015) | (0.011) |
| Tobin's Q | -0.006 | -0.003 | -0.003 | -0.002 |
| | (0.026) | (0.005) | (0.006) | (0.005) |
| ROA | 0.380 | 0.071 | 0.095 | 0.046 |
| | (0.284) | (0.054) | (0.068) | (0.054) |
| Leverage | 0.090 | -0.060 | -0.045 | -0.074* |
| | (0.173) | (0.043) | (0.051) | (0.043) |
| SG&A | -0.545 | 0.222*** | 0.237*** | 0.206*** |
| | (0.342) | (0.073) | (0.089) | (0.073) |
| Cash holdings | 0.226 | -0.087*** | -0.115*** | -0.060* |
| | (0.149) | (0.031) | (0.040) | (0.034) |
| Tangibility | 0.211 | -0.160*** | -0.172*** | -0.149*** |
| | (0.216) | (0.041) | (0.054) | (0.041) |
| Board independence | 0.303 | 0.051 | 0.013 | 0.088* |
| | (0.213) | (0.050) | (0.059) | (0.052) |
| CEO duality | 0.006 | -0.023** | -0.023** | -0.023** |
| | (0.045) | (0.009) | (0.011) | (0.009) |
| Institutional ownership | 0.089 | 0.025 | 0.002 | 0.048 |
| | (0.145) | (0.033) | (0.038) | (0.034) |
| Constant | -1.383** | | | |
| | (0.625) | | | |
| Firm FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| F statistics | 38.32 | | | |
| No. of observations | 5,164 | 5,164 | 5,164 | 5,164 |

**Table 6**
**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 7**
**Female analysts and E&S discussions on earnings conference calls**

This table examines the relation between female analyst coverage and analyst raising E&S-related questions on 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 on 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 8**
**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 | 0.000 | 0.001 | -0.001 |
| | (0.006) | (0.007) | (0.006) |
| Female more general experience | 0.009 | 0.010 | 0.008 |
| | (0.007) | (0.008) | (0.007) |
| N_female × Female more general experience | 0.018*** | 0.022*** | 0.015** |
| | (0.007) | (0.008) | (0.007) |
| Ln(1 + N_analysts) | -0.009** | -0.011** | -0.008* |
| | (0.005) | (0.005) | (0.005) |
| Other controls | YES | YES | YES |
| Constant | -0.606*** | -0.624*** | -0.589*** |
| | (0.034) | (0.038) | (0.034) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.555 | 0.518 | 0.507 |
| No. of observations | 20,423 | 20,423 | 20,423 |

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

| Variable | E&S score (1) | E score (2) | S score (3) |
|---|---|---|---|
| N_female | -0.002 | -0.001 | -0.003 |
| | (0.005) | (0.006) | (0.005) |
| Female more firm experience | 0.023*** | 0.023*** | 0.024*** |
| | (0.008) | (0.009) | (0.008) |
| N_female × Female more firm experience | 0.020*** | 0.024*** | 0.016*** |
| | (0.006) | (0.007) | (0.006) |
| Ln(1 + N_analysts) | -0.010** | -0.011** | -0.009** |
| | (0.005) | (0.005) | (0.005) |
| Other controls | YES | YES | YES |
| Constant | -0.604*** | -0.622*** | -0.586*** |

| | | | |
|---|---|---|---|
| | (0.034) | (0.038) | (0.034) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.557 | 0.520 | 0.509 |
| No. of observations | 20,423 | 20,423 | 20,423 |

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

| Variable | E&S score (1) | E score (2) | S score (3) |
|---|---|---|---|
| N_female | 0.012*** | 0.015*** | 0.008** |
| | (0.003) | (0.004) | (0.003) |
| Female star analyst | 0.047*** | 0.043** | 0.051*** |
| | (0.015) | (0.017) | (0.015) |
| N_female × Female star analyst | 0.003 | 0.005 | 0.001 |
| | (0.009) | (0.009) | (0.009) |
| Ln(1 + N_analysts) | -0.010** | -0.011** | -0.009* |
| | (0.005) | (0.005) | (0.005) |
| Other controls | YES | YES | YES |
| Constant | -0.606*** | -0.625*** | -0.588*** |
| | (0.034) | (0.038) | (0.034) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.555 | 0.518 | 0.508 |
| No. of observations | 20,423 | 20,423 | 20,423 |

**Table 9**
**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

| | E&S score | E score | S score |
|---|---|---|---|
| Variable | (1) | (2) | (3) |
| N_female | 0.012** | 0.011* | 0.013** |
| | (0.005) | (0.006) | (0.005) |
| N_female directors | 0.042*** | 0.039*** | 0.045*** |
| | (0.003) | (0.003) | (0.003) |
| N_female × N_female directors | -0.000 | 0.002 | -0.003 |
| | (0.002) | (0.002) | (0.002) |
| Ln(1 + N_analysts) | -0.010** | -0.011** | -0.009** |
| | (0.004) | (0.005) | (0.004) |
| Other controls | YES | YES | YES |
| Constant | -0.516*** | -0.539*** | -0.494*** |
| | (0.032) | (0.036) | (0.032) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.577 | 0.535 | 0.531 |
| No. of observations | 20,423 | 20,423 | 20,423 |

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

| | E&S score | E score | S score |
|---|---|---|---|
| Variable | (1) | (2) | (3) |
| N_female | 0.012*** | 0.015*** | 0.010** |
| | (0.004) | (0.005) | (0.004) |
| N_female executives | 0.018*** | 0.012** | 0.023*** |
| | (0.005) | (0.006) | (0.005) |
| N_female × N_female executives | 0.002 | 0.003 | 0.000 |
| | (0.004) | (0.005) | (0.004) |
| Ln(1 + N_analysts) | -0.002 | -0.002 | -0.002 |
| | (0.006) | (0.006) | (0.005) |
| Other controls | YES | YES | YES |
| Constant | -0.780*** | -0.850*** | -0.710*** |
| | (0.047) | (0.053) | (0.049) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.536 | 0.510 | 0.472 |
| No. of observations | 13,228 | 13,228 | 13,228 |

## 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 cutting-edge 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 on 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 2022), 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 (2022) 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 (2022) 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, 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 (i.e., an iteration of the entire training data set). 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.

*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.

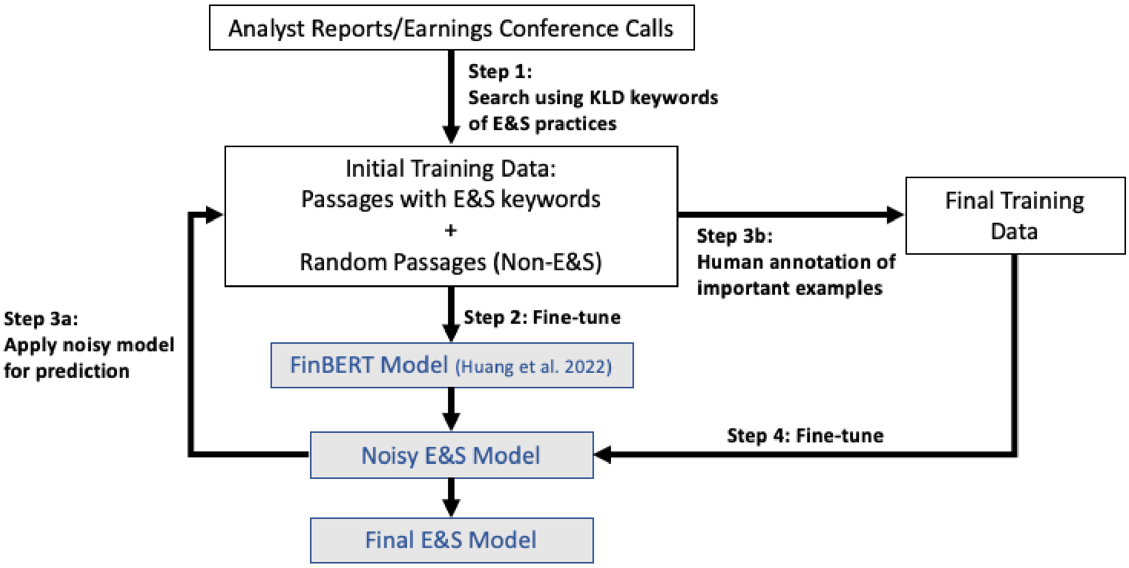


**Figure IA2**
**Temporal trends in E&S-related discussions in analyst reports and on earnings conference calls**

This figure plots the temporal trend in E&S-related discussions in analyst reports and E&S-related questions on 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.

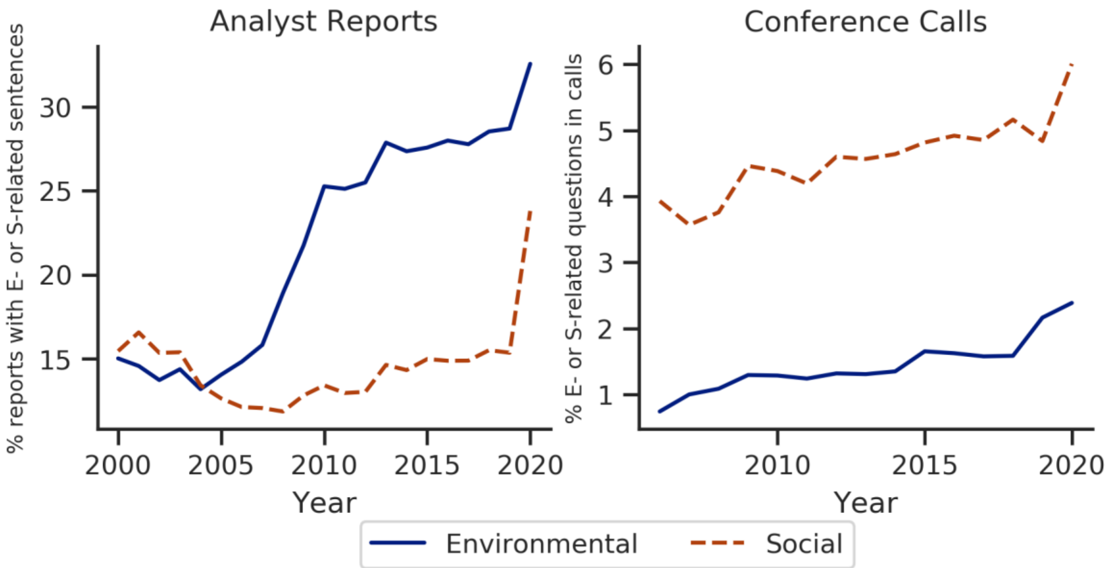


**Figure IA3**
**Distribution of E&S-related discussions in analyst reports and on earnings conference calls across Fama-French 12 industries**

This figure plots the distribution of E&S-related discussions in analyst reports and E&S-related questions on 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.

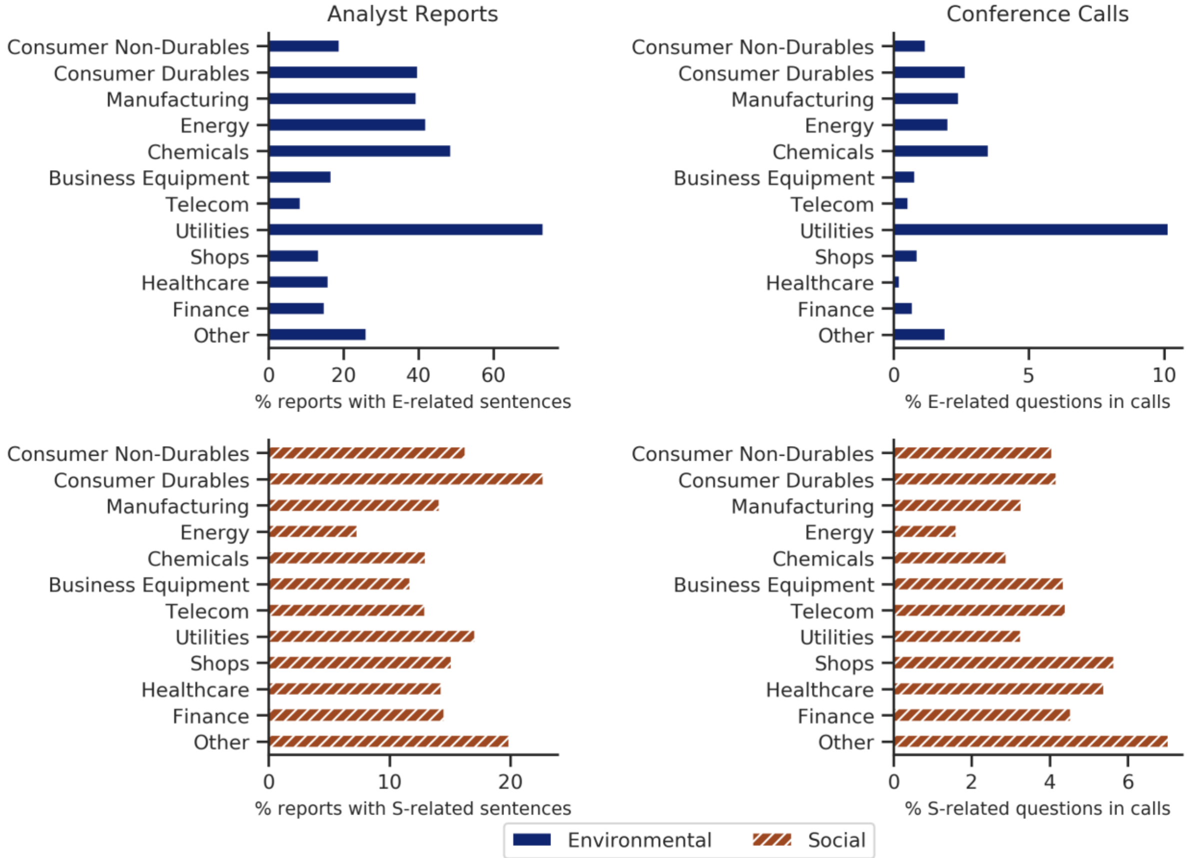
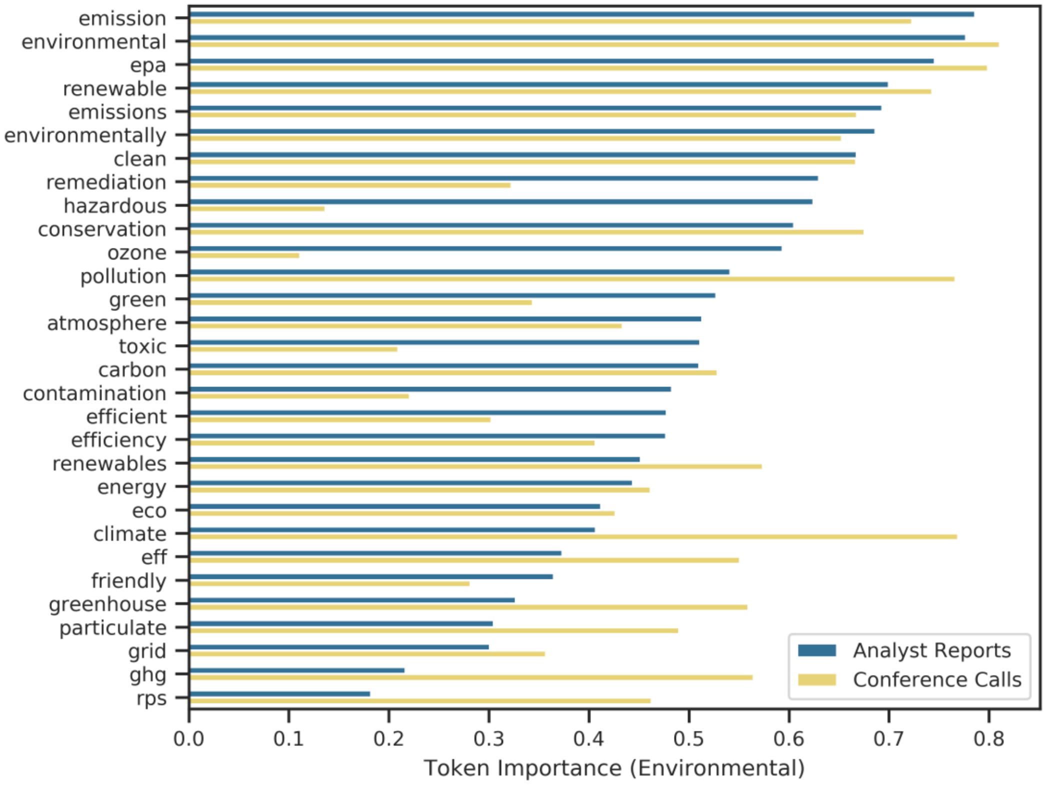


**Figure IA4**
**Most important tokens in fine-tuned FinBERT models**

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 tokenzied to *re* and *##sident*).

Panel A: Most important tokens regarding environmental issues



Panel B: Most important tokens regarding social issues

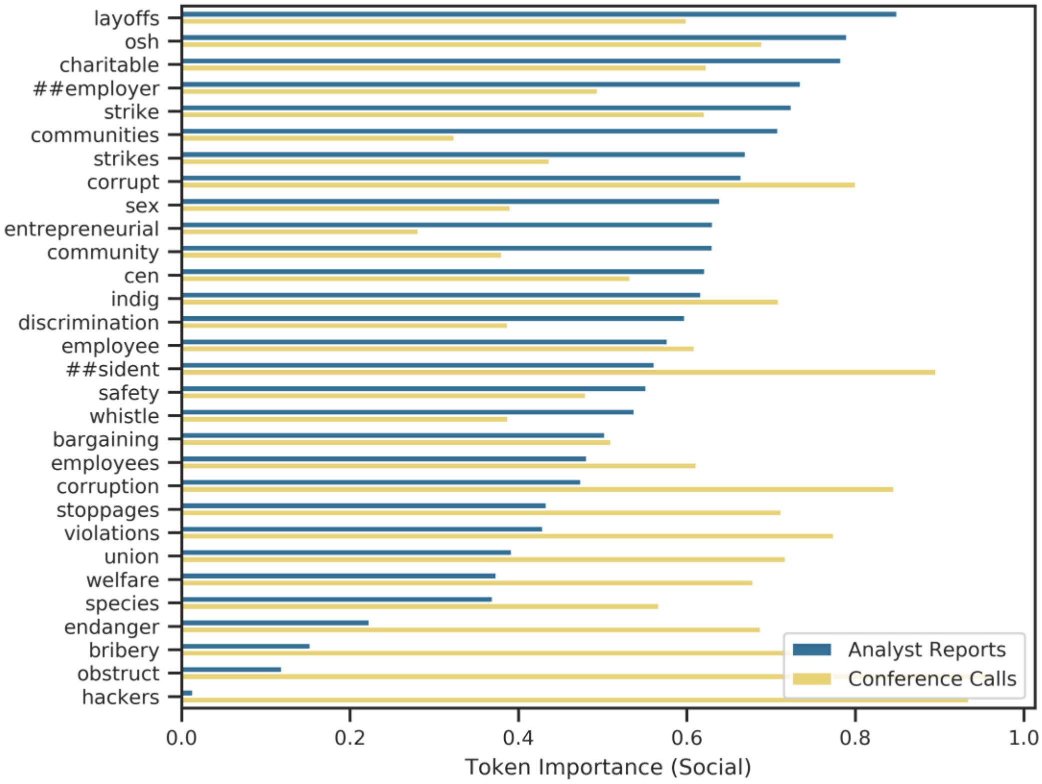


**Table IA1**
**Queries of E&S issues**

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**
**Examples of E&S-related sentences in analyst reports**

This table lists examples of E&S-related sentences in analyst reports used in Table 6. 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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>Regarding gender and racial/ethnic diversity, the company's board of directors is one-third female. |

**Table IA3**
**Examples of E&S-related questions on earnings conference calls**

This table lists examples of E&S-related questions on earnings conference calls used in Table 7. 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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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.<br><br>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 IA4**
**Robustness checks: Using an alternative measure of female analyst coverage**

This table conducts robustness checks on our main findings in Table 3 by using an alternative measure of female analyst coverage. *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. All other variables are the same as those in Table 3. 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 score (2) | S score (3) |
|---|---|---|---|
| Female analyst ratio | 0.039*** | 0.051*** | 0.027** |
| | (0.010) | (0.012) | (0.011) |
| Ln(1 + N_analysts) | -0.005** | -0.005** | -0.005** |
| | (0.002) | (0.002) | (0.002) |
| Firm size | 0.127*** | 0.130*** | 0.124*** |
| | (0.001) | (0.001) | (0.001) |
| Tobin's Q | 0.011*** | 0.011*** | 0.012*** |
| | (0.001) | (0.001) | (0.001) |
| ROA | 0.060*** | 0.027** | 0.095*** |
| | (0.009) | (0.011) | (0.010) |
| Leverage | -0.073*** | -0.070*** | -0.075*** |
| | (0.008) | (0.009) | (0.008) |
| SG&A | 0.129*** | 0.129*** | 0.128*** |
| | (0.009) | (0.010) | (0.009) |
| Cash holdings | -0.064*** | -0.051*** | -0.076*** |
| | (0.006) | (0.007) | (0.007) |
| Tangibility | -0.014* | 0.005 | -0.032*** |
| | (0.007) | (0.008) | (0.008) |
| Board independence | 0.009 | -0.002 | 0.020 |
| | (0.014) | (0.016) | (0.015) |
| CEO duality | -0.013*** | -0.012*** | -0.015*** |
| | (0.003) | (0.003) | (0.003) |
| Institutional ownership | -0.028*** | -0.044*** | -0.012* |
| | (0.006) | (0.006) | (0.006) |
| Constant | -0.616*** | -0.635*** | -0.596*** |
| | (0.015) | (0.017) | (0.016) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.553 | 0.516 | 0.506 |
| No. of observations | 20,423 | 20,423 | 20,423 |

**Table IA5**
**Robustness checks: Using an alternative measure of overall analysts following**

This table conducts robustness checks on our main findings in Table 3 by using an alternative measure of overall analysts following. *N_analysts* is the number of analysts covering a firm in a given year. All other variables are the same as those in Table 3. 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 score (2) | S score (3) |
|---|---|---|---|
| N_female | 0.014*** | 0.017*** | 0.011*** |
| | (0.004) | (0.004) | (0.004) |
| N_analysts | -0.002 | -0.001 | -0.002 |
| | (0.001) | (0.001) | (0.001) |
| Firm size | 0.126*** | 0.129*** | 0.123*** |
| | (0.003) | (0.003) | (0.003) |
| Tobin's Q | 0.011*** | 0.010*** | 0.011*** |
| | (0.002) | (0.002) | (0.002) |
| ROA | 0.059*** | 0.024 | 0.093*** |
| | (0.017) | (0.019) | (0.018) |
| Leverage | -0.073*** | -0.070*** | -0.075*** |
| | (0.016) | (0.018) | (0.017) |
| SG&A | 0.126*** | 0.126*** | 0.126*** |
| | (0.018) | (0.020) | (0.019) |
| Cash holdings | -0.064*** | -0.052*** | -0.076*** |
| | (0.012) | (0.013) | (0.012) |
| Tangibility | -0.014 | 0.005 | -0.032** |
| | (0.015) | (0.016) | (0.016) |
| Board independence | 0.013 | 0.003 | 0.022 |
| | (0.032) | (0.035) | (0.032) |
| CEO duality | -0.014** | -0.012* | -0.015** |
| | (0.006) | (0.007) | (0.006) |
| Institutional ownership | -0.030** | -0.046*** | -0.013 |
| | (0.011) | (0.013) | (0.012) |
| Constant | -0.613*** | -0.631*** | -0.595*** |
| | (0.034) | (0.038) | (0.034) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.553 | 0.517 | 0.506 |
| No. of observations | 20,423 | 20,423 | 20,423 |

**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 from 2005 to 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 from 2005 to 2018 when it was discontinued thereafter. Columns (7)-(9) present the results using the E&S scores from Morningstar's Sustainalytics over the period from 2009 to 2018 when the legacy Sustainalytics data set, which measures ESG preparedness and performance, was discontinued in 2019. 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** | 0.005*** | 0.003** | 0.006*** | 0.007*** | 0.008*** | 0.006*** |
| | (0.003) | (0.003) | (0.003) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Ln(1 + N_analysts) | -0.006 | -0.007 | -0.004 | 0.001 | 0.001 | 0.001 | -0.008*** | -0.009*** | -0.008*** |
| | (0.004) | (0.005) | (0.004) | (0.001) | (0.001) | (0.001) | (0.003) | (0.003) | (0.003) |
| Firm size | 0.095*** | 0.101*** | 0.090*** | 0.017*** | 0.016*** | 0.017*** | 0.039*** | 0.050*** | 0.028*** |
| | (0.002) | (0.003) | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) | (0.003) | (0.002) |
| Tobin's Q | 0.011*** | 0.010*** | 0.013*** | 0.003*** | 0.003*** | 0.003*** | 0.000 | 0.002 | -0.002 |
| | (0.002) | (0.003) | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) | (0.003) | (0.002) |
| ROA | 0.010 | 0.012 | 0.007 | 0.002 | 0.001 | 0.002 | 0.011 | -0.009 | 0.034* |
| | (0.018) | (0.021) | (0.019) | (0.005) | (0.005) | (0.006) | (0.018) | (0.024) | (0.018) |
| Leverage | -0.057*** | -0.066*** | -0.049*** | -0.019*** | -0.009* | -0.021*** | -0.016 | -0.016 | -0.017 |
| | (0.015) | (0.018) | (0.016) | (0.004) | (0.005) | (0.005) | (0.011) | (0.014) | (0.011) |
| SG&A | 0.128*** | 0.139*** | 0.117*** | 0.020*** | 0.015*** | 0.020*** | 0.073*** | 0.091*** | 0.056*** |
| | (0.019) | (0.023) | (0.019) | (0.004) | (0.004) | (0.005) | (0.020) | (0.026) | (0.018) |
| Cash holdings | -0.016 | 0.001 | -0.033** | -0.001 | 0.002 | -0.001 | 0.003 | 0.019 | -0.011 |
| | (0.014) | (0.017) | (0.014) | (0.003) | (0.003) | (0.004) | (0.014) | (0.018) | (0.012) |
| Tangibility | -0.021 | -0.019 | -0.024 | -0.008* | 0.005 | -0.010** | 0.001 | 0.012 | -0.010 |
| | (0.013) | (0.015) | (0.015) | (0.004) | (0.005) | (0.005) | (0.009) | (0.012) | (0.009) |
| Board independence | 0.021 | 0.010 | 0.033 | -0.014** | -0.009 | -0.015* | 0.030* | 0.030 | 0.030* |
| | (0.025) | (0.030) | (0.025) | (0.007) | (0.007) | (0.008) | (0.018) | (0.023) | (0.018) |
| CEO duality | -0.005 | -0.010 | 0.001 | -0.005*** | -0.002 | -0.006*** | -0.007* | -0.009* | -0.004 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (0.005) | (0.006) | (0.005) | (0.002) | (0.002) | (0.002) | (0.004) | (0.005) | (0.004) |
| Institutional ownership | -0.013 | -0.024* | -0.002 | -0.009** | -0.019*** | -0.007 | -0.012* | -0.023** | -0.003 |
| | (0.010) | (0.012) | (0.011) | (0.004) | (0.004) | (0.004) | (0.007) | (0.009) | (0.007) |
| Constant | -0.351*** | -0.412*** | -0.294*** | -0.129*** | -0.097*** | -0.135*** | 0.165*** | 0.048 | 0.283*** |
| | (0.031) | (0.037) | (0.031) | (0.010) | (0.012) | (0.011) | (0.025) | (0.033) | (0.026) |
| FF48 FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Adjusted $R^2$ | 0.459 | 0.395 | 0.409 | 0.314 | 0.186 | 0.318 | 0.332 | 0.341 | 0.300 |
| No. of observations | 14,449 | 14,449 | 14,449 | 23,772 | 23,772 | 23,772 | 8,618 | 8,618 | 8,618 |

**Table IA7**
**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. 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.

| | G score | G score | CSR strategy | CSR strategy | Management | Management | Shareholders | Shareholders |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| N_female | 0.003 | -0.001 | 0.022*** | 0.002 | 0.006 | 0.000 | 0.006 | -0.004 |
| | (0.002) | (0.002) | (0.004) | (0.003) | (0.004) | (0.003) | (0.005) | (0.003) |
| Ln(1 + N_analysts) | 0.001 | -0.003 | -0.024*** | -0.003 | -0.008 | 0.001 | -0.015*** | 0.002 |
| | (0.003) | (0.003) | (0.006) | (0.004) | (0.005) | (0.005) | (0.006) | (0.004) |
| Firm size | 0.038*** | 0.035*** | 0.130*** | 0.056*** | 0.050*** | 0.037*** | 0.019*** | -0.000 |
| | (0.002) | (0.005) | (0.003) | (0.007) | (0.003) | (0.008) | (0.003) | (0.007) |
| Tobin's Q | 0.003 | 0.000 | 0.011*** | 0.003 | 0.004* | -0.000 | 0.003 | 0.002 |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| ROA | 0.012 | 0.015 | 0.021 | 0.033 | 0.120*** | 0.034 | 0.021 | 0.005 |
| | (0.016) | (0.018) | (0.021) | (0.024) | (0.023) | (0.029) | (0.028) | (0.027) |
| Leverage | -0.035** | -0.003 | -0.078*** | -0.008 | -0.059*** | -0.012 | -0.028 | 0.014 |
| | (0.014) | (0.017) | (0.019) | (0.023) | (0.020) | (0.023) | (0.024) | (0.022) |
| SG&A | 0.046*** | 0.011 | 0.116*** | 0.024 | 0.090*** | 0.010 | -0.006 | -0.049* |
| | (0.015) | (0.020) | (0.021) | (0.024) | (0.021) | (0.028) | (0.029) | (0.027) |
| Cash holdings | -0.032*** | -0.036*** | -0.019 | 0.001 | -0.057*** | -0.022* | -0.050*** | 0.010 |
| | (0.011) | (0.009) | (0.014) | (0.011) | (0.014) | (0.012) | (0.016) | (0.013) |
| Tangibility | 0.006 | -0.032** | 0.012 | -0.027 | -0.018 | -0.029 | 0.055*** | -0.026 |
| | (0.013) | (0.014) | (0.017) | (0.018) | (0.019) | (0.021) | (0.021) | (0.022) |
| Board independence | 0.048* | -0.025 | 0.052 | -0.106*** | 0.253*** | 0.121*** | -0.020 | 0.023 |
| | (0.026) | (0.022) | (0.039) | (0.031) | (0.035) | (0.037) | (0.041) | (0.033) |
| CEO duality | -0.020*** | -0.015*** | -0.016** | -0.008 | -0.057*** | -0.037*** | -0.009 | -0.012* |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) | (0.007) |
| Institutional ownership | 0.059*** | 0.065*** | -0.082*** | 0.000 | 0.116*** | 0.068*** | 0.048*** | 0.014 |
| | (0.011) | (0.011) | (0.015) | (0.016) | (0.015) | (0.018) | (0.017) | (0.018) |
| Constant | 0.331*** | 0.433*** | -0.823*** | -0.146** | -0.133*** | 0.111 | 0.360*** | 0.502*** |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (0.029) | (0.045) | (0.042) | (0.064) | (0.039) | (0.073) | (0.047) | (0.060) |
| FF48 FE | YES | | YES | | YES | | YES | |
| Firm FE | | YES | | YES | | YES | | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Adjusted $R^2$ | 0.189 | 0.648 | 0.449 | 0.768 | 0.139 | 0.564 | 0.0464 | 0.665 |
| No. of observations | 20,423 | 19,990 | 20,423 | 19,990 | 20,423 | 19,990 | 20,423 | 19,990 |

**Table IA8**
**Controlling for Top5 institutional ownership**

This table conducts robustness checks on our main findings in Table 3 by controlling for institutional ownership by the five largest institutional shareholders instead of the overall institutional ownership (*Institutional Ownership*). *Top5 institutional ownership* is the fraction of shares outstanding held by the five largest institutional investors. All other variables are the same as those in Table 3. 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.

| | E&S score | E score | S score |
|---|---|---|---|
| Variable | (1) | (2) | (3) |
| N_female | 0.015*** | 0.019*** | 0.011*** |
| | (0.003) | (0.004) | (0.004) |
| Ln(1 + N_analysts) | -0.009** | -0.011** | -0.007 |
| | (0.005) | (0.005) | (0.004) |
| Firm size | 0.125*** | 0.127*** | 0.122*** |
| | (0.003) | (0.003) | (0.003) |
| Tobin's Q | 0.011*** | 0.010*** | 0.011*** |
| | (0.002) | (0.002) | (0.002) |
| ROA | 0.056*** | 0.018 | 0.094*** |
| | (0.017) | (0.019) | (0.018) |
| Leverage | -0.067*** | -0.064*** | -0.071*** |
| | (0.016) | (0.018) | (0.017) |
| SG&A | 0.126*** | 0.127*** | 0.126*** |
| | (0.018) | (0.020) | (0.019) |
| Cash holdings | -0.063*** | -0.050*** | -0.076*** |
| | (0.012) | (0.013) | (0.012) |
| Tangibility | -0.015 | 0.004 | -0.035** |
| | (0.015) | (0.016) | (0.016) |
| Board independence | 0.016 | 0.004 | 0.028 |
| | (0.032) | (0.035) | (0.032) |
| CEO duality | -0.013** | -0.012* | -0.015** |
| | (0.006) | (0.007) | (0.006) |
| Top5 institutional ownership | -0.091*** | -0.103*** | -0.079*** |
| | (0.023) | (0.026) | (0.024) |
| Constant | -0.596*** | -0.616*** | -0.576*** |
| | (0.034) | (0.038) | (0.034) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.554 | 0.517 | 0.507 |
| No. of observations | 20,423 | 20,423 | 20,423 |

**Table IA9**
**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 on 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 on 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) |
| 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) |
| 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 IA10**
**Subsample analysis: The Paris Agreement**

This table examines whether there is any temporal variation in the strength of the positive association between female analysts and corporate E&S performance. We conduct robustness checks on our main findings in Table 3 by dividing the sample period 2005–2021 into two sub-periods 2005–2015 and 2016–2021. We employ the same regression specification as that in Table 3. 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 over the period 2005–2015

| Variable | E&S score (1) | E score (2) | S score (3) |
|---|---|---|---|
| N_female | 0.015*** | 0.018*** | 0.011** |
| | (0.005) | (0.005) | (0.005) |
| Ln(1 + N_analysts) | -0.014** | -0.017** | -0.011* |
| | (0.006) | (0.007) | (0.006) |
| Firm size | 0.145*** | 0.152*** | 0.138*** |
| | (0.004) | (0.005) | (0.004) |
| Tobin's Q | 0.009** | 0.009* | 0.008* |
| | (0.004) | (0.005) | (0.005) |
| ROA | 0.107*** | 0.056 | 0.158*** |
| | (0.035) | (0.038) | (0.037) |
| Leverage | -0.097*** | -0.081** | -0.112*** |
| | (0.029) | (0.032) | (0.031) |
| SG&A | 0.266*** | 0.289*** | 0.244*** |
| | (0.044) | (0.049) | (0.045) |
| Cash holdings | -0.063** | -0.044 | -0.083*** |
| | (0.026) | (0.028) | (0.026) |
| Tangibility | -0.010 | 0.015 | -0.035 |
| | (0.023) | (0.024) | (0.024) |
| Board independence | 0.090** | 0.088* | 0.093** |
| | (0.044) | (0.048) | (0.044) |
| CEO duality | -0.016* | -0.017* | -0.014 |
| | (0.009) | (0.010) | (0.010) |
| Institutional ownership | -0.017 | -0.031 | -0.002 |
| | (0.018) | (0.020) | (0.018) |
| Constant | -0.899*** | -0.977*** | -0.821*** |
| | (0.055) | (0.060) | (0.056) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.497 | 0.468 | 0.446 |
| No. of observations | 8,831 | 8,831 | 8,831 |

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

| Variable | E&S score (1) | E score (2) | S score (3) |
|---|---|---|---|
| N_female | 0.010** | 0.014*** | 0.006 |
| | (0.004) | (0.005) | (0.004) |
| Ln(1 + N_analysts) | -0.007* | -0.006 | -0.009** |
| | (0.004) | (0.005) | (0.004) |

| | | | |
|---|---|---|---|
| Firm size | 0.115*** | 0.115*** | 0.114*** |
| | (0.002) | (0.003) | (0.002) |
| Tobin's Q | 0.014*** | 0.013*** | 0.014*** |
| | (0.002) | (0.002) | (0.002) |
| ROA | 0.032** | 0.001 | 0.063*** |
| | (0.015) | (0.017) | (0.017) |
| Leverage | -0.046*** | -0.048*** | -0.044*** |
| | (0.015) | (0.016) | (0.016) |
| SG&A | 0.068*** | 0.060*** | 0.075*** |
| | (0.015) | (0.016) | (0.016) |
| Cash holdings | -0.059*** | -0.050*** | -0.068*** |
| | (0.010) | (0.011) | (0.010) |
| Tangibility | -0.004 | 0.009 | -0.016 |
| | (0.015) | (0.016) | (0.016) |
| Board independence | -0.063** | -0.089** | -0.036 |
| | (0.031) | (0.035) | (0.032) |
| CEO duality | -0.014** | -0.010 | -0.018*** |
| | (0.006) | (0.006) | (0.006) |
| Institutional ownership | -0.018 | -0.031** | -0.005 |
| | (0.012) | (0.013) | (0.012) |
| Constant | -0.436*** | -0.415*** | -0.456*** |
| | (0.032) | (0.036) | (0.032) |
| FF48 FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Adjusted $R^2$ | 0.608 | 0.571 | 0.558 |
| No. of observations | 11,592 | 11,592 | 11,592 |