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Female Equity Analysts and Corporate Environmental and Social Performance

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Abstract. This paper examines the impact of female analyst coverage on firms' environmental and social (E&S) performance. Exploiting broker closures as a quasi-exogenous shock to analyst coverage, we find that firms experiencing an exogenous decline in female analyst coverage subsequently show a significantly larger drop in E&S scores than those experiencing an equivalent decline in male analyst coverage. To explore the underlying mechanisms, we develop novel machine-learning models to analyze more than 2.4 million analyst reports and 120,000 earnings call transcripts. Our analysis shows that, compared with their male counterparts, female analysts are more likely to address E&S issues, particularly those involving regulatory compliance, stakeholders, and the environment, in both research reports and earnings conference calls. They also display distinct cognitive and linguistic patterns when discussing E&S issues. Furthermore, female analysts are more likely to issue lower stock recommendations and target prices (lower stock recommendations) following negative E&S discussions in their reports (E&S incidents) than male analysts. Finally, investors respond more strongly to female analysts' negative tones when discussing E&S issues. Overall, our findings suggest that gender diversity among analysts plays a significant role in shaping corporate E&S practices and provide new insights into the origins of gender differences in skills within the equity analyst profession.

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1. Introduction

Sell-side equity analysts are known for their information discovery and interpretation roles, with implications for corporate investment and financing decisions (see, e.g., Derrien and Kecskés 2013, He and Tian 2013). Equity analysts also play an important governance role in scrutinizing management behavior (see, e.g., Yu 2008, Chen et al. 2015). Yet none of the existing research has taken a gender lens to explore the role of female analysts in monitoring corporate environmental and social (E&S) performance and delineating the underlying mechanisms.

Kumar (2010) argued that, because of perceived discrimination in the equity analyst profession, only women with superior abilities enter this field. He found that female analysts provide more accurate forecasts than their male counterparts and that the stock market reacts more strongly to forecast revisions made by female analysts. However, it remains unclear what explains these skill differences between female and male analysts. Motivated by surveys in both psychology and economics (Beutel and Marini 1995, Schwartz and Rubel 2005, Bertrand 2011) indicating that women, compared with men, tend to place greater emphasis on the well-being of others, their communities, and the environment, we examine whether female equity analysts are more likely to monitor a firm's E&S issues than their male counterparts and whether there are gender differences in research approaches, thus shedding light on the origins of gender differences in skills within the equity analyst profession.

In this paper, we leverage a large, unique data set of analyst research activities to investigate whether and how female analyst coverage influences corporate E&S performance. We employ a hand-collected sample of more than 11,000 sell-side equity analysts with gender data and various E&S measures from 2005 to 2021. We match the analyst data set with two large text corpora that represent analysts' primary research activities: more than 2.4 million analyst reports and 120,000 earnings call transcripts. Our empirical strategy proceeds in several steps.

First, we show that there is a positive and significant association between the number of female analysts covering a firm and that firm's E&S performance. For identification, we exploit broker closures as a quasi-exogenous shock to female (male) analyst coverage (Hong and Kacperczyk 2010, Kelly and Ljungqvist 2012, Chen et al. 2015). Following such an event, firms losing female analysts experience significant declines in E&S ratings relative to firms losing male analysts, suggesting a causal impact.

Next, we examine analysts' research activities—writing research reports and raising questions during earnings conference calls (Chen et al. 2015, Huang et al. 2018, Harford et al. 2019) to uncover the underlying mechanisms. We employ machine-learning tools to detect discussions of E&S topics in analyst reports and earnings call transcripts. Because E&S-related discussions encompass a broad range of topics and linguistic expressions, conventional keyword-based textual analysis methods are inadequate. We develop a new active learning approach to efficiently search for and annotate E&S-related discussions from the large corpora.[1] We then fine-tune the FinBERT model (Huang et al. 2023), a large language model trained on financial text, to create two tailored E&S text classification models that capture analysts' writing (in analyst reports) and raising questions (during earnings calls) about E&S issues.

We apply the models to analysts' main research activities, analyst reports and questions during earnings calls, to identify E&S-related passages. To examine the differences in how female and male analysts discuss E&S issues, we employ the Structural Topic Modeling (Roberts et al. 2014) to extract latent topics within those passages. We find substantial differences between female analysts' and male analysts' E&S discussions in both the intensity and thematic content. Female analysts discuss E&S topics more frequently and emphasize sustainability-relevant themes such as regulatory compliance, stakeholder welfare, and the environment, whereas male analysts focus more narrowly on financial considerations such as operational efficiency and performance. To examine gender differences in their cognitive and linguistic approaches to E&S issues, we employ the Linguistic Inquiry and Word Count software (Boyd et al. 2022). We find that female analysts employ more sophisticated cognitive processing in their E&S questions during calls and produce more readable analyses about E&S issues in their reports. These findings suggest that compared with male analysts, female analysts monitor broad E&S issues more closely and communicate E&S-related research more persuasively and clearly, which helps enhance the accessibility and impact of their E&S analyses.

Finally, we examine analysts' actions following their E&S-related research and/or firms' E&S incidents as well as how the market reacts to reports containing E&S discussions. We find that compared with male analysts, female analysts are more likely to issue lower stock recommendations and target prices (lower stock recommendations) following negative E&S discussions in their reports (firms' E&S incidents). Moreover, investors react more strongly to female analysts' negative tones in discussing a firm's E&S performance in their reports, which suggests that the market participants recognize the male-female skill differences in detecting E&S issues.

We conclude that female equity analysts play a unique monitoring role in enhancing corporate E&S performance through writing reports on E&S issues, raising questions about E&S issues during calls, and/or taking actions following firms' E&S issues (or E&S incidents). Our findings help shed light on the origins of male-female skill differences first established by Kumar (2010). Female analysts are more skilled at identifying value-relevant E&S issues than their male counterparts.

Our paper makes three contributions to the literature. First, our study contributes to the literature on gender and finance. Prior work shows that gender differences in values and preferences have implications for corporate investment decisions, financing policies, workplace practices, and corporate social responsibility (CSR) (see, e.g., Huang and Kisgen 2013; Matsa and Miller 2013; Levi et al. 2014, 2015; Tate and Yang 2015; Griffin et al. 2021; Hsu et al. 2025). Our paper establishes that female equity analyst coverage causally improves a firm's E&S performance. In doing so, we show that gender diversity among equity analysts serves as an impetus for firms to adopt more environmentally and socially responsible policies.

Second, our study contributes to the analyst literature, specifically the strand of the literature on the governance role of analysts (Yu 2008, Irani and Oesch 2013, Chen et al. 2015, Guo et al. 2019, Bradley et al. 2022, Jing et al. 2023). We extend this literature by taking a gender lens and identifying the specific mechanisms through which female analysts influence corporate E&S performance and by providing an explanation for the observed gender differences in analyst impact.

Finally, our study adds to the finance and accounting literature that employs computational linguistic methods to analyze large, unstructured data sets, particularly in the context of corporate environmental exposure (see, e.g., Kölbel et al. 2022, Sautner et al. 2023, Li et al. 2024). Several recent studies have adopted pretrained large language models like BERT (Devlin et al. 2019) for text classification (Kölbel et al. 2022, Huang et al. 2023). Our work differs from extant literature by incorporating the principles of data-centric AI, which emphasize that a high-quality training data set is just as critical as new modeling techniques (Whang et al. 2023, Zha et al. 2023). In this regard, our paper introduces a novel active learning approach that identifies domain-specific training examples from substantially larger and more diverse data sets than previously explored. Our approach, when combined with a pretrained large language model such as FinBERT (Huang et al. 2023), proves to be an effective strategy in accurately classifying text, particularly in situations when there is limited training data because of specialized language and terminology in diverse contexts. Leveraging computational linguistic methods and substantially larger data sets than prior studies (i.e., more than 2.4 million analyst reports and more than 120,000 earnings calls), we develop a novel active learning approach to accurately classify both environment- and social-related discussions in analyst research. Our findings reveal that gender differences in analyst impact stem from female analysts' greater propensity to monitor corporate E&S performance as well as their superior skills at persuasively and clearly communicating E&S issues compared with their male counterparts.

2. Hypothesis Development

Motivated by numerous studies across disciplines showing that, compared with men, women tend to exhibit stronger prosocial and altruistic preferences, hold greater benevolence and universalism values, and express heightened concern and responsibility for the well-being of others, their communities, and the environment (see, e.g., Beutel and Marini 1995, Schwartz and Rubel 2005, Bertrand 2011, Hsu et al. 2025), we posit that such gender difference in values and preferences may have implications for how female analysts monitor corporate E&S performance. Furthermore, Kumar (2010) found that female analysts are more skilled than their male counterparts, as evidenced by bolder and more accurate forecasts, and that market participants recognize this skill difference by responding more strongly to forecast revisions made by female analysts. Li et al. (2025) provided consistent evidence in an international context. Based on this, we argue that female analysts, relative to male analysts, may contribute to improved corporate E&S performance through more comprehensive assessment of E&S risks and opportunities and by exercising greater scrutiny to ensure that firms adopt more sustainable and socially responsible practices.

However, there are several reasons why female analysts may not care about or effectively monitor E&S issues. According to Kumar (2010), female analysts represent a unique group of competitive women who choose to pursue careers in the male-dominated financial services industry. As a result, female analysts might not share the same values and preferences as women in the general population. Supporting this idea, Adams and Funk (2012) found that female and male directors in Sweden differ systematically in their core values and risk attitudes in ways that are distinct from gender differences in the general population. Furthermore, consistent with established gender differences in overconfidence (Croson and Gneezy 2009), Comprix et al. (2022) demonstrated that female analysts are less aggressive in asserting their views during calls compared with their male counterparts. This behavioral trait could potentially mitigate any gender differences in monitoring E&S issues during calls, even if female analysts had placed greater emphasis on the well-being of others, their communities, and the environment than their male counterparts.

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

3. Sample Formation and Overview

3.1. Sample Formation

Because of the controversy surrounding aggregate ESG ratings (Berg et al. 2022), we measure corporate E&S performance using several approaches: the overall E&S score (and its component scores) from Refinitiv's ESG database (formerly known as Thomson Reuters' ASSET4 database), carbon emissions from S&P Global Trucost, and environmental and workplace safety/health violations from Violation Tracker. We measure *Carbon emissions* as the natural logarithm of one plus the sum of annual Scope 1 and Scope 2 carbon emissions, following Sautner et al. (2023). The Violation Tracker data on environment- and workplace safety- or health-related violations include civil and criminal cases from more than 40 federal regulatory agencies; we remove violations in which the penalty or settlement is lower than $5,000. We measure a firm's environmental (social) performance using both the dollar amount and frequency of environment-related (workplace safety-related) violation cases. *Environment-related penalties* is the natural logarithm of one plus the total dollar amount of penalty incurred because of a firm's environment-related violations in a given year. *Environment-related cases*, *Workplace safety-related penalties*, and *Workplace safety-related cases* are defined analogously. Table 1, panel A, lists the steps taken to form our main sample, comprising 20,423 firm-year observations representing 3,567 unique firms.

3.2. Identifying Female Equity Analysts

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

To unmask abbreviated brokerage names and analyst names from I/B/E/S, we manually search each brokerage's full name and its analysts from Capital IQ (supplemented by Bloomberg). Our matching process involves three steps: (1) We match abbreviated broker names in I/B/E/S (ESTIMID) to full broker names in Capital IQ based on resemblance; (2) we ascertain the match in Step 1 by matching analyst names in I/B/E/S (ANALYST) with those in Capital IQ using the last name and first name initial; and (3) we supplement the above two steps by checking whether Capital IQ analysts' stock coverage is the same as that by matched I/B/E/S analysts using Bloomberg's "*PEOP*" function. Of the 903 brokers in I/B/E/S, we are able to unmask full broker names for 866 (a 95.9% matching rate).

We then obtain individual analyst information, including biography and prefix (Mr. versus Ms.), from their employment history in Capital IQ (supplemented by BrokerCheck, LinkedIn, ZoomInfo, MarketScreener, and TipRanks). 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 11,753 out of the 12,640 unique analysts in the I/B/E/S Detail Recommendations file, achieving a 93.0% matching rate.

Table IA.1 in the Online Appendix provides an overview of female analysts over time and across Fama-French 12 industries over the period 2004–2020. It is worth noting that the patterns exhibited are largely consistent with those reported in Kumar (2010). The share of female analysts is relatively stable over our sample period, and female analysts are more heavily concentrated in the consumer nondurables, retail, healthcare, and utilities sectors.

3.3. Identifying Female Equity Analysts in Research Reports

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

To determine analyst gender in the analyst report sample, we match each analyst's name in Investext with our hand-collected gender data in the I/B/E/S-Capital IQ merged sample, as described in Section 3.2. Our matching process is as follows: (1) We match each broker in Investext to broker name and ID (EMASKCD) in the I/B/E/S-Capital IQ merged file; of the 822 unique brokers in Investext, we can link 300 brokers with EMASKCD—analysts affiliated with these 300 brokers produce 89% 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 that there is also a match with broker name-EMASKCD established in Step 1. In the end, we are able to uncover gender data for 6,641 analysts, representing 83% of the analysts affiliated with the 300 brokers in our analyst report sample.

After removing analyst reports with missing analyst-level control variables, our final sample comprises 985,295 reports covering 19,327 firm-year observations (representing 1,688 unique firms).

3.4. Identifying Female Equity Analysts in Earnings Conference Calls

We downloaded 129,302 earnings conference calls over the period 2007–2020 from Capital IQ. After matching with Compustat, we end up with 64,075 calls, covering 2,186 firms.[3]

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 the steps taken in Section 3.3. We can link 384 brokers with EMASKCD—analysts from these brokers represent an 83% share of the analysts attending calls in our call sample. In the end, we are able to uncover gender information for 4,897 analysts, representing 62% of the analysts from the 384 brokers in our call sample.

After removing analyst-call observations with missing analyst-level control variables, our final sample comprises 268,942 analyst-call observations from 52,104 earnings calls covering 14,361 firm-year observations for 1,348 unique firms.

3.5. Sample Overview

Table 1, panel B, 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. Online Appendix IA.B provides detailed variable definitions. We show that the sample mean/median E&S score is 0.420 (0.325), with the mean/ median E(S) score at 0.412/0.281 (0.427/ 0.355); the sample mean (median) carbon emissions (in millions of metric tons) is 1.221 (0.090); the sample

Table 1. Sample Formation and Summary Statistics

Panel A: Sample formation

	No. of firm-year obs.	No. of firm-year obs. removed	No. of 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

Panel B: Summary statistics

	Mean	5th percentile	Median	95th percentile	SD
E&S score	0.420	0.098	0.325	0.918	0.287
E score	0.412	0.098	0.281	0.937	0.312
S score	0.427	0.077	0.355	0.922	0.291
Carbon emissions (raw)	1,221,041	564	90,112	5,220,000	4,532,856
Environment-related penalties (raw)	425,158	0.000	0.000	1,069,000	2,289,046
Environment-related cases (raw)	0.887	0.000	0.000	4.000	1.668
Workplace safety-related penalties (raw)	97,236	0.000	6,695	203,495	486,467
Workplace safety-related cases (raw)	1.768	0.000	1.000	6.000	3.921
Carbon emissions	11.292	6.336	11.409	15.468	2.631
Environment-related penalties	4.504	0.000	0.000	13.882	5.681
Environment-related cases	0.415	0.000	0.000	1.609	0.588
Workplace safety-related penalties	5.989	0.000	8.809	12.223	5.121
Workplace safety-related cases	0.663	0.000	0.693	1.946	0.718
N_female	1.018	0.000	0.000	4.000	1.525
N_male	9.853	0.000	8.000	28.000	9.148
Having female analyst	0.469	0.000	0.000	1.000	0.499
Female analyst ratio	0.089	0.000	0.000	0.333	0.118
N_analyst	10.871	0.000	8.000	31.000	9.944
Total assets	16.965	0.158	3.572	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

Notes. This table describes sample formation steps and presents the summary statistics. Panel A reports the impact of various data matching steps and data filters on sample formation. Panel B presents the summary statistics of our main sample. The sample consists of 20,423 firm-year observations (representing 3,567 unique firms) with data on corporate E&S performance over the period 2005–2021.

mean (median) dollar amount of workplace safety-related penalties is 97.236 (6.695) thousand; and the sample mean (median) number of such cases is 1.768 (1). Our key variable of interest is *N_female*, the number of female equity analysts covering a firm. The mean/median is 1 (0). As a comparison, the mean/median number of male analysts covering a firm, *N_male*, is 10 (8); 46.9% of firm-year observations in our sample have at least one female equity analyst following, with an average female analyst ratio of 8.9%. Conditional on having female analyst coverage, the average female ratio of analysts is 15.6% (untabulated). It is worth noting that the mean/median number of analysts following, *N_analyst*, is 11 (8), which is fairly comparable to the mean/median of 9 (8) reported in Huang et al. (2018).[4]

4. Fine-Tuning FinBERT for Classifying E&S-Related Discussions via Active Learning

4.1. Why FinBERT?

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

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

In this paper, we fine-tune FinBERT to classify whether texts in analyst reports or questions during calls are related to E&S issues. Our goal is to classify a passage of text into one of three categories: Environmental (E), Social (S), or neither (Non-E&S).[5]

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

4.2. Constructing Domain-Specific Training Examples via Active Learning

We employ *active learning*—an algorithm that facilitates the efficient curation of domain-specific examples, thereby enabling the fine-tuning of two separate E&S text classification models, each designed specifically for analyst reports (calls) (Whang et al. 2023, Zha et al. 2023).

Figure IA.1 in the Online Appendix presents a flowchart of the active learning process. As shown in the figure, in Step 1, we use keywords related to E&S issues to search for a set of initial training examples from the two corpora.[6] Passages containing those keywords are tentatively labeled as positive examples (E or S), and random passages are used as negative examples (Non-E&S). In Step 2, we use the initial training examples to fine-tune the FinBERT model into a *Noisy E&S model*. In Step 3, we use the *Noisy E&S model* to classify the initial training examples. Given the *Noisy E&S model*'s output, a subset of important examples is labeled by human annotators (Cormack and Grossman 2014).[7] 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 Online Appendix that describes preprocessing and model training procedures step by step.

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

4.3. Capturing E&S-Related Discussions

After applying the fine-tuned FinBERT model to classify each sentence in an analyst report, we capture the frequency of discussions regarding E&S issues in a report using different indicator variables: *Having E&S sentences*, *Having E sentences*, and *Having S sentences*. These variables take the value of one if there is at least one relevant sentence in a report and zero otherwise. We capture the intensity of analysts discussing E&S issues by using the natural logarithm of one plus the number of sentences related to E&S performance in a report (*Ln*(*1* + *N_E&S sentences*), *Ln*(*1* + *N_E sentences*), and *Ln*(*1* + *N_S sentences*)). We obtain a similar set of measures for calls.[8]

Figures IA.2 and IA.3 in the Online Appendix offer overviews of the temporal trends and industry distributions of E&S-related discussions in reports and E&S-related questions during calls. Figure IA.2 reveals an overall upward trend in E&S discussions over the years. Notably, discussions pertaining to environmental issues in reports exhibit a significant uptick after 2008, probably driven by regulations outlined in the Presidential Climate Action Plan since 2008 and significant investments in clean energy outlined in the American Recovery and Reinvestment Act of 2009. We observe that whereas analysts tend to write more about environmental issues in their reports, they tend to raise more social questions during calls.[9] In terms of industry breakdown in Figure IA.3, 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 occur with a more even distribution across industries.

5. Main Results

5.1. Female Equity Analysts and Corporate E&S Performance

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

$$\begin{aligned} E\&S\ performance_{i,t+1} = \alpha + \beta_1 N\_female_{i,t} + \beta_2 N\_male_{i,t} \\ + \beta_3 Firm\ characteristics_{i,t} \\ + Industry \times Year\ FEs + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

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

5.1.1. Using Refinitiv E&S Scores. Table 2, panel A, presents the regression results when the dependent variables are *E&S score* and its component scores. We show that there is a positive and significant association between the number of female analysts following (*N_female*) and *E&S score*. In contrast, there is a negative and significant association between the number of male analysts following (*N_male*) and *E&S score*. Using the *t*-test to test the null that the coefficient on *N_female* is the same as the coefficient on *N_male,* that is, there is no gender difference in monitoring corporate E&S performance, the *p*-value shows that we reject the null. The negative association is consistent with the fact that because of gender differences in values and preferences, male analysts tend to focus on earnings, and that underinvestment in E&S performance can result in a boost in short-run performance, because investment in E&S performance is often taken as an item in SG&A expenses (Di Giuli and Kostovetsky 2014, Chen et al. 2020). These results provide new evidence suggesting that even among finance professionals, there remain gender differences in values and preferences relating to corporate E&S performance.[10]

In terms of economic significance, adding one more female analyst is associated with a 0.011 increase in *E&S score* (ranging from 0 to 1), which is equivalent to a 2.6% (0.011/0.420) increase relative to the mean E&S score, and a 3.8% (0.011/0.287) standard-deviation increase in *E&S score*.[11]

Prior studies show that greater analyst coverage reduces firms' emissions of toxic pollutants and injury rates in the workplace (see, e.g., Bradley et al. 2022, Jing et al. 2023). Our findings in Table 2, panel A, show that there is a gender difference in analyst monitoring of corporate E&S performance, which begs the question of the relationship between analyst coverage and corporate E&S performance. Table IA.8, panel A, in the Online Appendix presents the results. We show that using ratings to measure firms' E&S performance, there is no significant association between analyst coverage and firms' E&S performance.

In an alternative specification, we include firm and year fixed effects to control for time-invariant firm unobservables and time trends that might drive both female (male) analyst coverage and corporate E&S performance. Table IA.9, panel A, in the Online Appendix presents the regression results. We show that there remains a positive and significant association between *N_female* and *E&S score*.

As discussed earlier, we rely primarily on information from Capital IQ to determine analyst gender and to compute analyst coverage and female analyst coverage. To mitigate the problem of missing (unidentified) analysts, as a robustness check, we use *Female analyst ratio* or *Having female analyst* instead of the number of female analysts (*N_female*), assuming that this ratio in our identified analyst sample is a good proxy for the same ratio in the full analyst sample if the missing data problem in Capital IQ applies equally to both male and female equity analysts in the population. Table IA.9, panels B and C, presents the results. Our main findings remain.[12]

One might argue that our main findings are not due to the gender difference in values and preferences but the gender difference in political ideology.[13] It is well known that women are more likely to be Democratic-leaning than men, and Democratic-leaning individuals are more likely to care about E&S issues (Kaufmann and Petrocik 1999). Thus, it is important for us to rule out political ideology as an alternative explanation. Berry et al. (1998) developed a cross-validated, time-varying, state-level ideology score based on the roll call voting scores of state congressional delegations, the outcomes of congressional elections, the partisan division of state legislatures, the party of the governors, and various assumptions regarding voters and state political elites. To proxy for an analyst's political affiliation, we use the ideology score of the state in which an analyst's office is located as a proxy for his or her ideology. As a sanity check, we confirm that, using our proxy, there is a positive and significant association between female analysts and their leaning

Democratic. Table IA.9, panel F, presents the results. We show that after controlling for female/male analysts' ideology, there remain positive and significant associations between female analyst coverage and E&S (S) scores. Interestingly, there are positive and significant associations between male analysts' liberal views and E&S (E) scores, suggesting that political ideology might be behind some male analysts' focus on E&S issues. We caution readers about the crudeness of our proxy when interpreting this finding.[14]

5.1.2. Using Real E&S Outcomes. Table 2, panel B, presents the regression results when the dependent variables are measures of real E&S outcomes. We show that there is a negative and significant association between the number of female analysts following a firm (*N_female*) and each of the five measures of real E&S outcomes. Interestingly, and also in contrast to panel A, we show that there is a negative and significant association between the number of male analysts following a firm (*N_male*) and its frequency of environment-related cases, its dollar amount of penalties incurred because of workplace safety/health violations, and its frequency of workplace violation cases. Using the *t*-test to test the null that the coefficient on *N_female* is the same as the coefficient on *N_male*, that is, there is no gender difference in monitoring those real E&S outcomes, the *p*-value shows that we reject the null for three out of the five measures,

Table 2. Analyst Gender and Corporate E&S Performance

Panel A: Analyst gender and corporate E&S performance

Variable	E&S score (1)	E score (2)	S score (3)
N_female	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)
N_male	−0.001*	−0.001	−0.001*
	(0.001)	(0.001)	(0.001)
Firm size	0.125***	0.128***	0.122***
	(0.003)	(0.003)	(0.003)
Tobin's Q	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)
ROA	0.055***	0.017	0.093***
	(0.018)	(0.019)	(0.019)
Leverage	−0.074***	−0.071***	−0.077***
	(0.017)	(0.018)	(0.018)
SG&A	0.129***	0.128***	0.129***
	(0.018)	(0.020)	(0.019)
Cash holdings	−0.062***	−0.049***	−0.075***
	(0.012)	(0.013)	(0.012)
Tangibility	−0.011	0.006	−0.027*
	(0.015)	(0.016)	(0.016)
Board independence	0.010	−0.005	0.026
	(0.032)	(0.036)	(0.032)
CEO duality	−0.014**	−0.013*	−0.016**
	(0.006)	(0.007)	(0.006)
Institutional ownership	−0.030**	−0.047***	−0.014
	(0.012)	(0.014)	(0.012)
t-test [N_female = N_male]			
p-value	0.000	0.001	0.000
Industry × year FE	Yes	Yes	Yes
Adjusted R^2	0.560	0.522	0.516
No. of observations	20,402	20,402	20,402

Panel B: Analyst gender and real E&S outcomes

Variable	Carbon emissions (1)	Environment-related penalties (2)	Environment-related cases (3)	Workplace safety-related penalties (2)	Workplace safety-related cases (3)
N_female	−0.025*	−0.218***	−0.026***	−0.106*	−0.025***
	(0.013)	(0.065)	(0.007)	(0.060)	(0.009)
N_male	−0.005	−0.010	−0.005**	−0.056***	−0.006**
	(0.004)	(0.018)	(0.003)	(0.018)	(0.003)
Firm size	0.984***	1.132***	0.148***	0.704***	0.143***
	(0.023)	(0.120)	(0.019)	(0.110)	(0.021)

Table 2. (Continued)

Panel B: Analyst gender and real E&S outcomes

Variable	Carbon emissions (1)	Environment-related penalties (2)	Environment-related cases (3)	Workplace safety-related penalties (2)	Workplace safety-related cases (3)
Tobin's Q	−0.034**	0.206*	0.021*	−0.110	−0.018
	(0.014)	(0.118)	(0.012)	(0.110)	(0.016)
ROA	1.676***	−1.926	−0.020	3.552***	0.368**
	(0.159)	(1.243)	(0.145)	(1.177)	(0.186)
Leverage	0.233*	0.160	−0.026	−1.372**	−0.144
	(0.129)	(0.583)	(0.067)	(0.583)	(0.095)
SG&A	0.973***	0.255	0.068	0.955	0.233*
	(0.133)	(0.864)	(0.084)	(0.798)	(0.123)
Cash holdings	−0.505***	−1.541**	−0.119	−2.594***	−0.301***
	(0.097)	(0.736)	(0.077)	(0.748)	(0.109)
Tangibility	0.991***	3.177***	0.302***	0.821	0.207**
	(0.137)	(0.567)	(0.066)	(0.557)	(0.090)
Board independence	0.376**	3.202***	0.349***	0.728	0.063
	(0.187)	(1.015)	(0.120)	(0.995)	(0.162)
CEO duality	0.048	−0.131	−0.014	0.473***	0.050
	(0.036)	(0.189)	(0.023)	(0.181)	(0.031)
Institutional ownership	−0.013	−0.714	−0.085	−0.397	−0.091
	(0.087)	(0.461)	(0.058)	(0.439)	(0.084)
t-test [N_female = N_male]					
p-value	0.147	0.003	0.003	0.438	0.056
Industry × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.873	0.330	0.376	0.270	0.334
No. of observations	14,651	5,167	5,167	5,167	5,167

Notes. This table examines the relation between female analyst coverage (*N_female*) and firms' E&S performance. Panel A examines the relation between female analyst coverage and firms' E&S performance: *E&S score*, *E score*, and *S score*. Panel B examines the relation between female analyst coverage and real E&S outcomes: *Carbon emissions*, *Environment-related penalties*, *Environment-related cases*, *Workplace safety-related penalties*, and *Workplace safety-related cases*. Industry fixed effects are based on Fama-French 48-industry classifications. Definitions of the variables are provided in Online Appendix IA.B. Standard errors (in parentheses) are clustered at the firm level.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

Environment-related penalties, *Environment-related cases*, and *Workplace safety-related cases*, suggesting that female analysts are significantly more likely to identify the occurrence of environmental and workplace safety/health violation cases than their male counterparts.

Table IA.8, panel B, repeats the analysis in Table 2, panel B, using analyst coverage. Consistent with prior studies showing that greater analyst coverage improves firms' emissions and workplace safety records (see, e.g., Bradley et al. 2022, Jing et al. 2023), we show that there are negative and significant associations between analyst coverage (*N_analyst*) and bad real E&S outcomes.

We conclude that both male and female analyst coverage are significantly associated with real E&S outcomes and that only the female analyst coverage is positively and significantly associated with firms' overall E&S performance.

5.2. Identification Strategy: A DID Approach

5.2.1. A Quasi-Natural Experiment: Broker Closures. To assess whether the identified association between a firm's female equity analysts following and that firm's E&S performance is likely to be causal, we exploit a quasi-natural experiment, broker closures, where terminations of female (male) analyst coverage are the result of broker closures. Identification requires that such terminations correlate with a drop in female (male) analysts but do not otherwise correlate with corporate E&S performance. Following Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012), Chen et al. (2015), and Cen et al. (2021), we employ a sample of broker closures that are driven by either economic challenges in the equity research industry or mergers. To ensure that we capture a clean causal effect from a drop in female analyst coverage on firms' E&S performance instead of a causal effect from a drop in analyst coverage in general (irrespective of the gender of the exited analyst), we employ a sample of treated firms that experienced an exogenous drop in female analyst coverage and a sample of control firms that experienced an exogenous drop in male analyst coverage.[15]

To identify broker closures over the period 2005–2020, we proceed as follows. First, using both the I/B/E/S Recommendations Stop file and the I/B/E/S Detail History—Stop Estimates file, we obtain a list of brokers that stopped providing stock recommendations and/or estimates.[16] We keep brokers only if (1) their last recommendation (estimate) was made before or in 2020 or (2) they stopped providing recommendations (estimates) for more than 10 firms within any of the prior six months before the last month that they appeared in either of the stop files. If a broker appeared in both stop files around the same time, we treat it as one broker closure. Second, we merge the list of broker closures with our matched broker ID-broker name link file to ensure that we have information about analysts who worked with those brokers. We drop brokers with only one analyst with information on gender (to remove small brokers). Third, to identify the exact dates of broker closures due to mergers, we start with a sample of completed deals involving financial institution targets from the SDC Mergers and Acquisitions (M&A) database over the period 2005–2020. Specifically, we define a deal involving financial institutions if its target primary SIC code is "6211" ("Investment Commodity Firms, Dealers, and Exchanges"). We include only completed deals whose completion date is between January 1, 2005, and December 31, 2020. We match I/B/E/S broker names with target firm names in SDC. Given that matching at the target firm level fails to capture deals that take place at its parent level, we manually check the unmatched brokers using online sources. Finally, for the remaining closure cases, we first search a broker's closure date in Factiva and the Financial Industry Regulatory Authority's (FINRA) BrokerCheck database. Because FINRA does not always provide the exact date of a broker's closure, we further search Capital IQ to verify the status of each exited broker and/or whether its research division is out of business. We end up with 133 broker closure events, 60 of which were due to mergers. We use the last time that these brokers appeared in either of the I/B/E/S stop files as the closure event date used in our DID analysis because I/B/E/S has the most accurate information about when a broker stops equity research.

5.2.2. Identifying the Treated and Control Firms. To form the treated firm sample, following Kelly and Ljungqvist (2012) and Cen et al. (2021), we first identify analysts who worked for those brokers that disappeared from the I/B/E/S Unadjusted Detail History file (by not issuing earnings forecasts) in the year after a broker's closure date.[17] Second, we further classify affected analysts as those who were covering a firm at least one year before a closure event and were not covering the same firm one year after the closure event, using AMASKCD as the unique analyst identifier. For example, a male analyst with AMASKCD 9985 from AG Edwards, Inc., was covering Carnival Corporation (ticker: "CCL") from 2005 to 2007, and AG Edwards, Inc., was acquired by Wachovia Corporation in 2007. However, the analyst switched jobs to Wells Fargo and continued to cover Carnival Corporation at Wells Fargo. This analyst cannot be treated as "affected" by a broker closure event, and Carnival Corporation did not experience an exogenous drop in male analyst coverage, even though it was covered by a male analyst from an exited broker. In another example, a female analyst with AMASKCD 113,881 from Lehman Brothers was covering Crown Holdings, Inc. (ticker "CCK"), from 2006 to 2008. In 2008, Lehman Brothers went bankrupt, and the analyst no longer covered Crown Holdings, Inc. Afterward. In this case, we can confidently say that Crown Holdings was covered by an affected female analyst and thus experienced an exogenous drop in female analyst coverage. We further restrict the sample to firms that were indeed affected by one of the 133 broker closure events. A total of 99 closure events out of the initial 133 broker closure events remain after this step, 47 of which were due to mergers. On average, a closure event affects 7.7 analysts, comprising 0.8 female analysts and 6.9 male analysts.

Third, we further keep firms with at least a two-year gap between two consecutive broker closure events that affected them. We remove firms that (1) missed analyst coverage information either before or after a closure event, (2) lost both the female and male analyst coverage in the same year because of the same closure event, and (3) did not experience a drop in (female/male) analyst coverage between the year before a closure event and the year after. We keep only the firm-year observations in the year before a closure event and the year after.[18]

Finally, we merge firms covered by those exited brokers with the baseline sample of 20,423 firm-year observations in Table 2, panel A, and retain only firms that have non-missing E&S scores and control variables in both one year before ($t-1$) and one year after ($t+1$), following Chen et al. (2015).[19] The sample consists of five treated firms associated with two broker closure events and 58 potential control firms associated with 17 broker closure events.

We further use propensity score matching to match each treated firm with five control firms without replacement based on firm characteristics in the year before a closure event. We use all firm characteristics to estimate the propensity score as in Table 2, panel A, except for CEO duality, because this indicator variable equals 1 for every treated firm before the treatment. Our final sample for the DID analysis consists of five treated firms associated with two broker closure events and 25 control firms associated with 13 broker closure events for a total of 60 ($=2\times(5+25)$) firm-year observations and 13 unique broker closure events. Table IA.10, panel A, provides a detailed description of the sample formation process.

Table IA.10, panel B, lists the 13 broker closure events, the number of the treated firms previously covered by a female analyst from an exited broker, and the number of the control firms previously covered by a male analyst from an exited broker. We note that the average number of analysts following the treated (control) firms is 8.6 (12.2) before the treatment and 8 (9.76) after. The median number of analysts following the treated (control) firms is 9 (10) before the treatment and 9 (7) after.

5.2.3. The DID Regression. To investigate the effect of an exogenous drop in female analyst coverage, relative to that of an exogenous drop in male analyst coverage, on corporate E&S performance, we employ a DID specification as follows:

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

where $Treated_i$ is an indicator variable that takes the value of one if firm i experienced an exogenous drop in female analyst coverage because of a broker closure event, and zero firm i experienced an exogenous drop in male analyst coverage because of a broker closure event. $Post_{i,t}$ is an indicator variable that takes the value of one in the year after a broker closure ($t+1$) and zero in the year before ($t-1$). The standalone indicator is absorbed by our inclusion of firm fixed effects, and the post indicator is absorbed by our inclusion of year fixed effects. Firm and year fixed effects are included to control for time-invariant firm characteristics and temporal trends, respectively.

Table 3 presents the results examining the effect of an exogenous drop in female analyst coverage on corporate E&S performance. We show that the coefficient on the interaction term *Treated* × *Post* is negative and significant, suggesting that an exogenous drop in female equity analyst coverage leads to a significant decrease in corporate E&S performance.[20]

Table 3. Analyst Gender and Corporate E&S Performance: A DID Approach

Variable	E&S score (1)	E score (2)	S score (3)
Treated × post	−0.138***	−0.153**	−0.122*
	(0.039)	(0.058)	(0.067)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.926	0.873	0.829
No. of observations	60	60	60

Notes. The table examines the effect of an exogenous drop in female analyst coverage due to broker closures on corporate E&S performance. The sample consists of 60 firm-year observations (10 treated firm-year observations and 50 control firm-year observations, using propensity score matching). *Treated* is an indicator variable that takes the value of 1 if a firm loses one female analyst from a broker closure during that year, and their female analyst coverage decreases between the year before the closure event and the year after the closure event. Treated takes the value of zero if a firm loses one male analyst from a broker closure during that year, and their male analyst coverage decreases between the year before the closure event and the year after the closure event. *Post* is an indicator variable that takes the value of 1 in the year after a broker's closure ($t+1$) and zero in the year before ($t-1$). Standard errors (in parentheses) are clustered at the firm level.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

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

6. The Mechanisms

Analysts have several potential means of influencing the firms that they cover. One such means is through their research reports. These reports provide analysts with an opportunity to express concerns about a firm's E&S issues. Another is through interactions with management during earnings conference calls, in which analysts pose questions about various aspects of a firm's business operations, including its E&S practices. The third is through taking actions following their E&S-related discussions or firms' E&S incidents.

Based on these potential means of influence, we propose two possible monitoring mechanisms through which female equity analysts could help shape corporate E&S performance. The first mechanism is "voice," whereby, compared with their male counterparts, female analysts not only engage in more discussions in their reports or pose more questions about a firm's E&S issues but also exhibit distinct cognitive and linguistic patterns in their communications with firms that might be more effective. The second mechanism is "action," whereby female analysts are more likely to issue lower stock recommendations following negative E&S discussions in their reports and/or negative developments in firms' E&S performance (e.g., E&S incidents). Both mechanisms could work together or independently. These actions will put pressure on firms to improve their E&S performance in order to maintain favorable analyst coverage and recommendations.

To capture analysts' voices, we apply the fine-tuned FinBERT models described in Section 4 to capture analysts' discussions of E&S issues in reports and questions about E&S issues during calls and explore any gender differences in cognitive and linguistic patterns (Boyd et al. 2022). To capture analysts' actions, we examine whether there are gender differences in analysts' stock recommendations and target price forecasts following their negative discussions of E&S issues in reports and/or E&S incidents. Finally, we also explore whether investors are paying (more) attention to female analysts' E&S-related discussions in their reports.

6.1. E&S Issues in Analyst Reports

Table 4, panel A, presents the summary statistics at the report level. We show that 20.5% of the reports in our sample touch upon firms' E&S issues and that the average number of E&S-related sentences in a report is 0.5 (among reports discussing E&S issues, the average number of E&S-related sentences in a report increases to 2.6 (untabulated)). Analysts are more likely to write about environmental issues than social issues. The probability

Table 4. Analyst Gender and E&S Discussions in Analyst Reports

Panel A: Summary statistics at the report level

	Mean	5th percentile	Median	95th percentile	SD
Having E&S sentences (×100)	20.455	0.000	0.000	100.000	40.337
Having E sentences (×100)	13.034	0.000	0.000	100.000	33.667
Having S sentences (×100)	10.335	0.000	0.000	100.000	30.442
N_E&S sentences	0.534	0.000	0.000	3.000	2.296
Ln(1 + N_E&S sentences)	0.213	0.000	0.000	1.386	0.469
N_E sentences	0.340	0.000	0.000	2.000	1.924
Ln(1 + N_E sentences)	0.133	0.000	0.000	1.099	0.375
N_S sentences	0.194	0.000	0.000	1.000	0.994
Ln(1 + N_S sentences)	0.092	0.000	0.000	0.693	0.286
N_sentences	68.377	13.000	57.000	159.000	48.552
Female	0.110	0.000	0.000	1.000	0.313

Panel B: Analyst gender and E&S discussions in reports

Variable	Having E&S sentences (×100) (1)	Having E sentences (×100) (2)	Having S sentences (×100) (3)	Ln(1 + N_E&S sentences) (4)	Ln(1 + N_E sentences) (5)	Ln(1 + N_S sentences) (6)
Female	0.823***	0.317	0.617***	0.007*	0.003	0.005**
	(0.307)	(0.250)	(0.223)	(0.004)	(0.003)	(0.002)
Education	0.306**	0.143	0.210**	0.003*	0.001	0.002**
	(0.126)	(0.096)	(0.099)	(0.001)	(0.001)	(0.001)
CFA	0.013	0.143	0.119	0.001	−0.001	0.004**
	(0.233)	(0.186)	(0.180)	(0.003)	(0.002)	(0.002)
Star analyst	−0.811**	−0.580*	−0.686**	−0.009**	−0.007**	−0.005*
	(0.401)	(0.309)	(0.303)	(0.005)	(0.003)	(0.003)
Forecast frequency	−0.307***	−0.219***	−0.209***	−0.005***	−0.003***	−0.002***
	(0.035)	(0.030)	(0.026)	(0.000)	(0.000)	(0.000)
Forecast horizon	0.007***	0.006***	0.004***	0.000***	0.000***	0.000***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
No. of firms followed	0.006	0.009	−0.003	0.000	0.000	−0.000
	(0.018)	(0.015)	(0.013)	(0.000)	(0.000)	(0.000)
No. of industries followed	0.190***	0.182***	0.014	0.002**	0.002***	0.000
	(0.068)	(0.056)	(0.053)	(0.001)	(0.001)	(0.001)
General experience	0.066**	0.068***	0.022	0.001**	0.001***	−0.000
	(0.029)	(0.021)	(0.023)	(0.000)	(0.000)	(0.000)
Firm × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.224	0.280	0.154	0.277	0.339	0.159
No. of observations	985,295	985,295	985,295	985,295	985,295	985,295

Notes. This table examines the relation between female analyst coverage and discussions of E&S issues in analyst reports. Our sample consists of 985,295 reports covering 19,327 firm-year observations (representing 1,688 unique firms). We employ different indicator variables (*Having E&S sentences*, *Having E sentences*, and *Having S sentences*) that take the value of 1 if there is at least one relevant sentence in an analyst report and zero otherwise. We also capture the intensity of E&S discussions by using the natural logarithm of one plus the number of relevant sentences in an analyst report (*Ln(1 + N_E&S sentences)*, *Ln(1 + N_E sentences)*, and *Ln(1 + N_S sentences)*). Panel A presents the summary statistics at the report level. Panel B presents report-level regressions examining the relation between analyst gender and their E&S discussions in reports. Definitions of the variables are provided in Online Appendix IA.B. Standard errors (in parentheses) are clustered at the analyst times year level.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

for the former is 13.0%, whereas the probability for the latter is 10.3%.

Table 4, panel B, presents the regression analysis at the report level. 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 0.8-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 20.5%, representing a 3.9% (0.8%/20.5%) increase.

6.2. E&S Questions During Earnings Conference Calls

Table 5, panel A, presents the summary statistics at the analyst-call level. We show that 15.3% of the analysts ask about firms' E&S issues during calls and that the average

Table 5. Analyst Gender and E&S Discussions During Earnings Conference Calls

Panel A: Summary statistics at the analyst-call level

	Mean	5th percentile	Median	95th percentile	SD
Having E&S questions (×100)	15.303	0.000	0.000	100.000	36.002
Having E questions (×100)	3.935	0.000	0.000	0.000	19.443
Having S questions (×100)	12.044	0.000	0.000	100.000	32.547
N_E&S questions	0.183	0.000	0.000	1.000	0.473
Ln(1 + N_E&S questions)	0.116	0.000	0.000	0.693	0.280
N_E questions	0.045	0.000	0.000	0.000	0.237
Ln(1 + N_E questions)	0.028	0.000	0.000	0.000	0.137
N_S questions	0.139	0.000	0.000	1.000	0.403
Ln(1 + N_S questions)	0.090	0.000	0.000	0.693	0.247
N_questions	2.956	1.000	3.000	6.000	1.761
Female	0.091	0.000	0.000	1.000	0.288

Panel B: Analyst gender and E&S discussions during calls

Variable	Having E&S questions (×100) (1)	Having E questions (×100) (2)	Having S questions (×100) (3)	Ln(1 + N_E&S questions) (4)	Ln(1 + N_E questions) (5)	Ln(1 + N_S questions) (6)
Female	0.931***	0.099	0.754***	0.007***	0.001	0.006***
	(0.304)	(0.144)	(0.273)	(0.002)	(0.001)	(0.002)
Education	0.224**	0.100*	0.175*	0.002**	0.001**	0.001**
	(0.103)	(0.054)	(0.091)	(0.001)	(0.000)	(0.001)
CFA	0.047	−0.142	0.166	−0.000	−0.001	0.001
	(0.183)	(0.091)	(0.164)	(0.001)	(0.001)	(0.001)
Star analyst	0.644*	0.644***	0.194	0.005*	0.004***	0.001
	(0.378)	(0.195)	(0.330)	(0.003)	(0.001)	(0.002)
Forecast frequency	0.057	0.021	0.046	0.000*	0.000	0.000
	(0.036)	(0.019)	(0.032)	(0.000)	(0.000)	(0.000)
Forecast horizon	0.001	−0.000	0.001*	0.000	−0.000	0.000**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
No. of firms followed	0.025	0.016**	0.012	0.000	0.000**	0.000
	(0.016)	(0.008)	(0.014)	(0.000)	(0.000)	(0.000)
No. of industries followed	−0.068	−0.009	−0.071	−0.000	−0.000	−0.001
	(0.060)	(0.032)	(0.052)	(0.000)	(0.000)	(0.000)
General experience	0.106***	0.021**	0.096***	0.001***	0.000**	0.001***
	(0.021)	(0.010)	(0.019)	(0.000)	(0.000)	(0.000)
Firm × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.008	0.037	0.018	0.008	0.037	0.018
No. of observations	268,942	268,942	268,942	268,942	268,942	268,942

Notes. This table examines the relation between female analyst coverage and analysts raising E&S-related questions during earnings conference calls. Our sample consists of 268,942 analyst-call observations from 52,104 earnings calls covering 14,361 firm-year observations (representing 1,348 unique firms). We employ different indicator variables (*Having E&S questions*, *Having E questions*, and *Having S questions*) that take the value of 1 if an analyst raises at least one relevant question during a call and zero otherwise. We also capture the intensity of E&S questions by using the natural logarithm of one plus the number of relevant questions by an analyst during a call (*Ln(1 + N_E&S questions)*, *Ln(1 + N_E questions)*, and *Ln(1 + N_S questions)*). Panel A presents the summary statistics at the analyst-call level. Panel B presents the analyst-call-level regressions examining the relation between analyst gender and their E&S-related questions during calls. Definitions of the variables are provided in Online Appendix IA.B. Standard errors (in parentheses) are clustered at the analyst times year level.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

number of E&S-related questions in a call is 0.2 (among calls with E&S-related questions, the average number of E&S-related questions in a call is 1 (untabulated)). Analysts are more likely to ask questions about social issues than environmental issues. The probability of the former is 12.0%, whereas the probability of the latter is 3.9%.

Table 5, panel B, presents the regression analysis at the analyst-call level. 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 0.931-percentage-point increase in the probability of analysts asking about E&S issues. This effect is economically large given that the sample average probability is 15.3%, representing a 6% (0.9%/15.3%) increase.

6.3. Gender Differences in Analytical Approaches to Discussing E&S Issues

To investigate whether and how female and male analysts differ in discussing E&S issues, we analyze the thematic, cognitive, and linguistic characteristics of E&S-related passages identified by our FinBERT models. This analysis allows us to uncover distinctive gender differences in E&S themes and analytical and communicative patterns that help explain female analysts' effectiveness in monitoring corporate E&S performance.

First, we employ the Structural Topic Modeling (STM) (Roberts et al. 2014) to identify latent topics within analyst reports and earnings call questions while explicitly modeling the relationship between analyst gender and topic prevalence. The details of our STM analysis are provided in the Online Appendix. This approach allows us to examine whether and how E&S issues raised by female and male analysts differ thematically.

Figure 1 plots the differences in E&S topics emphasized by female and male analysts in reports and during calls. Table 6 lists a selection of top words for each topic in each corpus, along with our assigned labels.

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

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

These findings indicate that female analysts adopt a more holistic, stakeholder-oriented perspective when discussing E&S issues, considering factors such as regulatory compliance, risk management, and customer impacts. In contrast, male analysts tend to take a more shareholder-oriented perspective, emphasizing metrics related to profitability, efficiency, and market positioning. Furthermore, female analysts' E&S discussions are likely to be more impactful because of their focus on strategically important topics such as capital projects and brand loyalty.

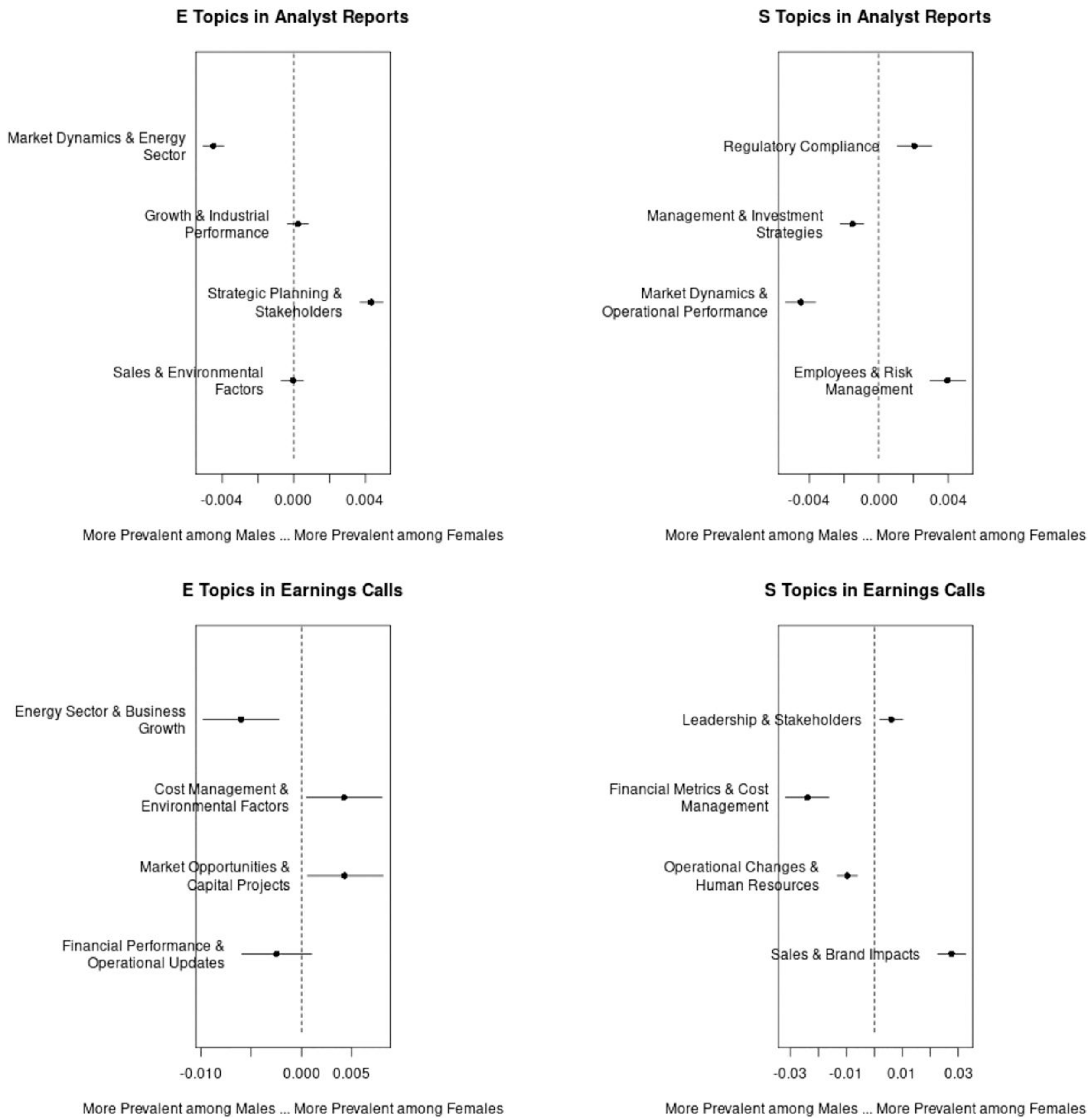
Second, we use the Linguistic Inquiry and Word Count (LIWC) software (Boyd et al. 2022; see a recent finance application in Li et al. 2021) to examine the cognitive dimensions of language, focusing on categories such as causal reasoning and insight that reveal an analyst's analytical depth. These LIWC metrics offer insight into an analyst's cognitive processing and persuasive ability. Prior research shows that the use of cognitive words reflects the depth of an individual's thinking (Tausczik and Pennebaker 2010). For example, a higher frequency of causal words (e.g., *how*, *because*) and insight words (e.g., *know*, *think*) can indicate active reappraisal and sense-making. In our context, this suggests that an analyst is going beyond merely stating facts to explaining the financial materiality of E&S issues through cause-and-effect reasoning. This interpretation aligns with Li et al. (2025), who found that analyst reports featuring more cause-and-effect reasoning tend to be more influential. Although specific word categories serve only as proxies for cognitive processes rather than direct measures of skill, we argue that they nonetheless shed light on an analyst's ability to convey information persuasively. Table 7, panels A and B, presents the regression results for these LIWC measures.

For analyst reports, we find that gender differences are limited to causal words. Female analysts use significantly more causal words than their male counterparts. For earnings call questions, we find significant gender differences in cognitive language use. Female analysts exhibit higher scores in overall cognition, cognitive processes, insight words, and causal words. These results indicate that during the spontaneous interactions of earnings calls, female analysts employ more complex cognitive processing when raising questions about E&S issues. The gender differences in LIWC measures are more pronounced during earnings calls than in analyst reports, which is likely due to the spontaneous nature of the former that allows analysts' cognitive patterns to emerge naturally.

Third, we examine whether female and male analysts differ in readability of their E&S discussions in reports. We employ two established readability metrics: the Gunning-Fog Index, where a lower score indicates greater readability, and the Flesch Reading Ease Index, where a higher score indicates greater readability, as well as a composite readability index, where a higher score indicates greater readability.[21]

Table 7, panel C, presents the regression results. The findings indicate that E&S discussions by female analysts are associated with higher readability scores compared with those by male analysts. This suggests that female

Figure 1. Analyst Gender and E&S Topics



Notes. This figure plots the differences in topic proportions between female and male analysts in analyst reports and during earnings calls. The horizontal bar represents the magnitude of the difference, with positive values indicating topics that are more prevalent among female analysts and negative values indicating topics that are more prevalent among male analysts. The whisker depicts the 95% confidence interval for each difference. The topic labels are based on the most prevalent and distinctive words associated with each topic, as determined by the Structural Topic Modeling (STM) analysis and listed in Table 6.

analysts may communicate E&S-related content more clearly, potentially improving the accessibility and influence of their analyses.[22]

We conclude that when discussing E&S issues, female analysts employ more sophisticated cognitive processing during questioning and communicate with greater clarity in their writing. As a result, it is possible that investors will respond differently to female analysts compared with male analysts regarding E&S issues, a conjecture that we will test when examining price reactions to the release of analyst reports in Section 6.6.

6.4. Gender Differences in Actions Following Negative E&S Discussions

We use the pretrained FinBERT-tone model from Huang et al. (2023) to classify sentiment (positive, negative, and

Table 6. Analyst Gender and E&S Topics

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

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

neutral) in E&S-related sentences in reports. At the sentence level, we capture tone by employing an indicator variable, *Tone*, that takes the value of 1 if the probability of positive sentiment is greater than 50%, −1 if the probability of negative sentiment is greater than 50%, and zero otherwise. At the report level, *Negative E&S tone* is the negative value of the average tone of E&S-related sentences. *Negative non-E&S tone* is defined analogously. We examine whether there is any gender difference in analysts' research output following their negative discussions of E&S issues. Table 8 presents the results at the report level.

We show that the coefficient on the interaction term *Female* × *Negative E&S tone* is negative and significant when the dependent variable is stock recommendation (target price), suggesting that female analysts are more likely to issue lower stock recommendations (target prices) compared with male analysts having negative

Table 7. Analyst Gender and Analytical Approaches to Discussing E&S Issues

Panel A: Analyst gender and their cognitive language usage in discussing E&S issues in reports

Variable	Cognition (1)	All-or-one (2)	Cognitive processes (3)	Insight (4)	Causation (5)
Female	−0.081	−0.002	−0.024	−0.010	0.103***
	(0.124)	(0.009)	(0.095)	(0.037)	(0.036)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm × year FE	Yes	Yes	Yes	Yes	Yes
Broker × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.175	0.126	0.207	0.146	0.187
No. of observations	160,158	160,158	160,158	160,158	160,158

Panel B: Analyst gender and their cognitive language usage in raising E&S-related questions during calls

Variable	Cognition (1)	All-or-one (2)	Cognitive processes (3)	Insight (4)	Causation (5)
Female	0.519***	−0.042*	0.309**	0.213***	0.104*
	(0.176)	(0.025)	(0.154)	(0.081)	(0.053)
Other controls	Yes	Yes	Yes	Yes	Yes
Firm × year FE	Yes	Yes	Yes	Yes	Yes
Broker × year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.064	0.034	0.073	0.046	0.055
No. of observations	27,378	27,378	27,378	27,378	27,378

Panel C: Analyst gender and readability of their E&S discussions in reports

Variable	Gunning-Fog index (1)	Flesch reading ease score (2)	Readability (3)
Female	−0.189**	1.035***	0.357***
	(0.084)	(0.323)	(0.077)
Other controls	Yes	Yes	Yes
Firm × year FE	Yes	Yes	Yes
Broker × year FE	Yes	Yes	Yes
Adjusted R^2	0.252	0.224	0.284
No. of observations	160,172	160,172	160,172

Notes. This table examines the relation between analyst gender and cognitive and linguistic patterns in discussing E&S issues. Panel A presents the report-level regressions examining the relation between analyst gender and their cognitive language usage in discussing E&S issues in reports. The sample consists of 160,158 reports covering 15,594 firm-year observations (representing 1,633 unique firms). Panel B presents the analyst-call level regressions examining the relation between analyst gender and their cognitive language usage in raising E&S-related questions during calls. The sample consists of 27,378 calls covering 10,402 firm-year observations (representing 1,318 unique firms). Panel C presents the report-level regressions examining the relation between analyst gender and readability of their E&S discussions in reports. The sample consists of 160,172 reports covering 15,595 firm-year observations (representing 1,633 unique firms). Definitions of the variables are provided in Online Appendix IA.B. Standard errors (in parentheses) are clustered at the analyst time year level.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

E&S discussions in reports. In terms of economic significance, a change in *Negative E&S tone* from neutral to negative (or from positive to neutral) by female analysts is associated with a 3.0% drop in stock recommendations (0.021/0.689, where 0.689 is the sample mean of stock recommendations) and a 0.5% drop in target prices (0.006/1.208, where 1.208 is the sample mean of target prices) compared with their male counterparts. We further show that the coefficient on the interaction term *Female* × *Negative E&S tone* is not significantly different from zero when the dependent variable is earnings forecast. We conclude that compared with male analysts, female analysts are more likely to issue lower stock recommendations and target prices, following negative E&S discussions in their reports.

6.5. Gender Differences in Stock Recommendations Following E&S News Events

A central hypothesis in our study is that, because of gender differences in values and preferences, female analysts are more likely to monitor corporate E&S issues than their male counterparts (regardless of whether they address E&S practices in their reports or raise E&S-related questions during calls). In this section, we explore a setting in which female analysts may be more responsive to firms' E&S incidents by updating their research output more frequently than their male counterparts.

We use incident-level data from RepRisk and keep only E&S-related incidents. We then merge the report-level analyst research output data with the RepRisk data,

Table 8. Analyst Gender, E&S-Related Discussions in Reports, and Analysts' Research Output

Panel A: Summary statistics at the report level

	Mean	5th percentile	Median	95th percentile	SD
Recommendation	0.689	0.000	1.000	2.000	0.831
Target price	1.208	0.844	1.178	1.646	0.270
Earnings forecast	5.051	0.008	5.245	10.663	3.832
Negative E&S tone	−0.004	−0.500	0.000	0.500	0.310
Negative non-E&S tone	−0.085	−0.403	−0.065	0.179	0.173
Female	0.109	0.000	0.000	1.000	0.311

Panel B: Analyst gender, tones in E&S-related discussions in reports, and their research output

Variable	Recommendation (1)	Target price (2)	Earnings forecast (3)
Female × Negative E&S tone	−0.021*	−0.006*	−0.033
	(0.012)	(0.003)	(0.022)
Female	−0.006	−0.009***	0.009
	(0.008)	(0.002)	(0.010)
Negative E&S tone	−0.008**	−0.003***	0.013*
	(0.004)	(0.001)	(0.007)
Negative non-E&S tone	−0.865***	−0.209***	−0.312***
	(0.011)	(0.003)	(0.015)
Report length	0.015***	0.001*	−0.001
	(0.002)	(0.001)	(0.003)
Star analyst	0.000	0.012***	0.005
	(0.012)	(0.003)	(0.014)
Education	0.007*	0.001	0.002
	(0.004)	(0.001)	(0.005)
CFA	−0.006	−0.002	−0.014**
	(0.006)	(0.002)	(0.007)
Forecast frequency	0.017***	0.001***	−0.003**
	(0.001)	(0.000)	(0.001)
Forecast horizon	−0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
No. of firms followed	−0.001	0.000*	−0.001***
	(0.000)	(0.000)	(0.001)
No. of industries followed	0.011***	0.001**	0.003
	(0.002)	(0.001)	(0.002)
General experience	0.004***	0.001***	0.001
	(0.001)	(0.000)	(0.001)
Firm × year FE	Yes	Yes	Yes
Broker × year FE	Yes	Yes	Yes
Adjusted R^2	0.434	0.547	0.876
No. of observations	707,594	658,659	665,950

Notes. This table examines the relation between analyst gender, tones in E&S-related discussions in reports, and their stock recommendations, target prices, and earnings forecasts at the report level. The recommendation sample consists of 707,594 reports covering 17,988 firm-year observations (representing 1,648 unique firms) over the period 2004–2020. The target price sample consists of 658,659 reports covering 17,618 firm-year observations (representing 1,661 unique firms) over the period 2004–2020. The earnings forecast sample consists of 665,950 reports covering 18,037 firm-year observations (representing 1,665 unique firms) over the period 2004–2020. Panel A presents the summary statistics at the report level. Panel B presents the report-level regressions examining the relation between analyst gender, E&S-related discussions in reports, and research output. Definitions of the variables are provided in Online Appendix IA.B. Standard errors (in parentheses) are clustered at the analyst time year level.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

using a window of 90 days prior to a report's release date. We employ three measures of an E&S news event: severity, novelty, and reach (influence). We also create an indicator variable, *Saliency*, that takes the value of one if an incident's severity score is more than one, its novelty score is more than one, or its reach score is more than one and zero otherwise. We examine whether there is any gender difference in analysts' stock recommendations following a firm's E&S incidents.[23] Table 9 presents the results at the report level.

We show that the coefficients on the interaction term between *Female* and E&S news severity/novelty/saliency are negative and significant, suggesting that female analysts are more likely to issue lower stock recommendations compared with male analysts when their covered firms have E&S incidents.

Table 9. Analyst Gender, E&S News Events, and Stock Recommendations

Panel A: Summary statistics at the report level

	Mean	5th percentile	Median	95th percentile	SD
Recommendation	0.702	0.000	1.000	2.000	0.829
Severity	0.313	0.000	0.000	1.750	0.601
Novelty	0.337	0.000	0.000	2.000	0.646
Reach	0.395	0.000	0.000	2.000	0.770
Saliency	0.199	0.000	0.000	1.000	0.399
Female	0.108	0.000	0.000	1.000	0.310

Panel B: Analyst gender, E&S news events, and stock recommendations

Variable	Recommendation (1)	Recommendation (2)	Recommendation (3)	Recommendation (4)
Female	0.005	0.004	0.002	0.004
	(0.010)	(0.010)	(0.010)	(0.010)
Female × severity	−0.020*			
	(0.010)			
Severity	0.004			
	(0.003)			
Female × novelty		−0.015*		
		(0.009)		
Novelty		0.001		
		(0.002)		
Female × reach			−0.009	
			(0.009)	
Reach			0.001	
			(0.002)	
Female × saliency				−0.028*
				(0.015)
Saliency				0.004
				(0.004)
Other controls	Yes	Yes	Yes	Yes
Firm × year FE	Yes	Yes	Yes	Yes
Broker × year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.408	0.408	0.408	0.408
No. of observations	631,472	631,472	631,472	631,472

Notes. This table examines the relation between analyst gender, a firm's RepRisk E&S news events, and its analysts' stock recommendations at the report level. The sample consists of 631,472 reports covering 15,844 firm-year observations (representing 1,635 unique firms associated with 14,852 RepRisk E&S news events) over the period 2007–2020. Panel A presents the summary statistics at the report level. Panel B presents the report-level regressions examining the relation between analyst gender, E&S news events, and research output. Definitions of the variables are provided in Online Appendix IA.B. Standard errors (in parentheses) are clustered at the analyst time year level.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

6.6. The Information Content of Analysts' E&S Discussions

To investigate the information content of analysts' E&S discussions in reports, we conduct an event study relating three-day cumulative abnormal returns (CAR) around the report date, *CAR[−1,+1]*, to measures of analysts' E&S discussions controlling quantitative and qualitative summary measures of a report and analyst and firm characteristics (Huang et al. 2014, Huang et al. 2018).[24] Table 10 presents the regression results.

We show that the coefficient on the interaction term *Female × Negative E&S tone* is negative and significant, suggesting that female analysts' E&S discussions in a report provide information beyond that provided by its quantitative and qualitative measures. In other words, the stock market participants are aware of the male-female skill differences regarding identifying E&S issues, and they respond more strongly to E&S issues raised by female analysts. In terms of economic significance, a change in *Negative E&S tone* from neutral to negative (or from positive to neutral) by female analysts is associated with a three-day abnormal negative return of 20.4 basis points, corresponding to a $22.8 million decrease in market value for an average firm in the sample, compared with their male counterparts.[25] It is worth noting that the effect documented above is the direct information effect of female analysts' E&S discussions in reports and that there are also indirect effects via changing stock recommendations and target prices shown in Table 8.

In summary, our analyses in this section establish a clear link between female analysts' research activities

Table 10. Analyst Gender and Information Content of E&S-Related Discussions in Reports

Panel A: Summary statistics for the key variables

	Mean	5th percentile	Median	95th percentile	SD
CAR[−1,+1] (%)	0.131	−5.032	0.081	5.433	3.220
Negative E&S tone	−0.025	−1.000	0.000	1.000	0.659
Negative non-E&S tone	−0.096	−0.390	−0.089	0.174	0.168
Female	0.097	0.000	0.000	1.000	0.296

Panel B: Analyst gender and price reactions to analyst reports

Variable	CAR[−1,+1] (1)	CAR[−1,+1] (2)
Female × negative E&S tone	−0.209**	−0.204**
	(0.103)	(0.102)
Female	−0.151**	−0.118*
	(0.075)	(0.072)
Negative E&S tone	−0.079**	0.033
	(0.032)	(0.033)
Negative non-E&S tone		−1.421***
		(0.132)
Report length		0.047
		(0.029)
Recommendation revision		0.889***
		(0.064)
Target price revision		3.114***
		(0.440)
Earnings forecast revision		1.476***
		(0.270)
Prior CAR		0.010**
		(0.005)
Other analyst/firm controls	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.001	0.027
No. of observations	26,525	26,525

Notes. This table examines the relation between analyst gender and information content of analysts' E&S-related discussions at the report level. The sample comprises reports that contain an earnings forecast revision and are not issued at the same time as other reports on the same firm or as any other major corporate announcements over the period 2004–2020. Our sample consists of 26,525 reports covering 6,949 firm-year observations (representing 1,243 unique firms). Panel A presents the summary statistics for the key variables. Panel B presents the regression results. Industry fixed effects are based on Fama-French 12-industry classifications. Definitions of the variables are provided in Online Appendix IA.B. Standard errors (in parentheses) are double-clustered at the firm and analyst levels.

***Statistical significance at the 1% level; **statistical significance at the 5% level; *statistical significance at the 10% level.

and their monitoring role in corporate E&S performance. We find that female analysts not only focus more on E&S issues in their writings and questions but also exhibit systematically different thematic emphases and analytical styles compared with their male counterparts. These differences in perspective and focus lead to tangible outcomes, with investors reacting significantly more to female analysts' negative tones in E&S discussions and female analysts more likely to take action by issuing lower stock recommendations and target prices (lower stock recommendations) following negative E&S discussions (E&S incidents). Ultimately, these findings suggest that female analysts' distinct voice and action translate into improved E&S ratings for the firms they cover and that our analysis sheds new light on the origins of gender differences in skills first identified by Kumar (2010).

7. Conclusions

Using a hand-collected sample of more than 11,000 sell-side equity analysts with gender data and both E&S ratings and real E&S outcomes over the period 2005–2021, we show that there is a positive and significant association between the number of female analysts covering a firm and that firm's E&S performance. Using broker closures as an exogenous shock to the number of female (male) analysts following, our difference-in-differences analysis suggests that female analyst coverage has a causal effect on firms' E&S performance.

To delineate the mechanisms through which female analysts help improve corporate E&S performance, we adopt an active learning approach to fine-tune FinBERT models in order to uncover E&S-related discussions in analysts' research activities. We then apply the Structural Topic Modeling and Linguistic Inquiry and Word Count analyses to help capture thematic, cognitive, and linguistic differences between female and male analysts in discussing E&S issues. We find that female analysts are more likely to discuss firms' E&S issues in reports and during calls and that female analysts adopt a more stakeholder-oriented perspective than their male counterparts. When discussing E&S issues, female analysts employ more sophisticated cognitive processing during questioning and communicate with greater clarity in their writing. We further show that, following negative E&S-related discussions in reports (E&S incidents), female equity analysts are more likely to issue lower stock recommendations and target prices (lower stock recommendations) than their male counterparts and that investors react significantly more to female analysts' negative tones in discussing E&S issues in their reports.

To the best of our knowledge, we are among the first in the literature to link analysts' research activities with their monitoring using machine learning and big data. We find that female equity analysts play a distinct monitoring role in corporate E&S performance, and our results provide new insights into gender differences in skills in the equity analyst profession (Kumar 2010).

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Endnotes

[1] In a nutshell, active learning uses a preliminary model to help select domain-specific training examples that are likely to be most useful for improving the model. In the process, we iteratively label training examples and refine the model. As a result, active learning, which uses a smaller yet high-quality training data set, is more efficient than other fine-tune algorithms. See Section 4 and our technical appendix in the Online Appendix for details.

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

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

[4] Table IA.2 in the Online Appendix provides the Pearson correlation matrix. Examination of the correlation matrix suggests that multicollinearity is unlikely to be an issue.

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

[6] Table IA.3 in the Online Appendix lists queries of corporate E&S issues.

[7] Table IA.4 in the Online Appendix lists some important examples identified by active learning protocols for human labeling.

[8] Table IA.5 in the Online Appendix provides examples of E&S-related sentences identified in reports. Table IA.6 in the Online Appendix provides examples of E&S-related questions identified in calls.

[9] 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 et al. (2017) and Bolton and Kacperczyk (2021). In contrast, social performance is more controversial and harder to quantify and, as a result, is more likely to be raised during calls. Second, earnings calls and analyst reports play distinctly different roles in shaping a firm's information environment, whereby the former provides a platform for analysts to question unclear firm policies and practices, whereas the latter incorporates all value-relevant information into a report. Hence, analysts tend to provide relatively more discussion on environmental issues in their reports and ask more clarifying questions about social issues during calls. Consistent with the above argument, Figure IA.4 in the Online Appendix shows different E&S issues discussed in reports versus those raised during calls.

[10] Table IA.7 in the Online Appendix presents the results from our main specification in Equation (1), using alternative data sets to measure E&S performance: Thomson Reuters' ASSET4, MSCI's KLD Stats, and Morningstar's Sustainalytics. We show that our main findings remain.

[11] This economic significance is comparable to other important factors identified in prior literature. For example, Dyck et al. (2019) found that a one-standard-deviation increase in a firm's institutional ownership is associated with a 4.5% increase in its environmental performance. Hsu et al. (2025) showed that a one-standard-deviation increase in the share of female directors on corporate boards is associated with a 4% increase in its environmental performance. This economic significance is also comparable to other control variables in our baseline regression. We find that the economic significance of *N_female* (i.e., the change in E&S score driven by adding one more female analyst) is higher than that driven by a one-standard-deviation increase in *N_male*, *ROA*, *Tangibility*, *Board independence*, *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*.

[12] One possible interpretation of our main findings is that they are not due to gender differences in values but to the organizational culture of a brokerage with which a female analysis is affiliated. For example, a large brokerage might be under more scrutiny to promote diversity, inclusion, and CSR than a small one. Consistent with this conjecture, the share of female analysts at the top 10 brokers is 15.7%, and the share of female analysts at the non-top 10 brokers is 11.0% in our sample. To examine this possible interpretation, we repeat our analysis by replacing our female analyst coverage variable with two measures: coverage by female analysts from the top 10 brokers (by size) and that from the non-top 10 brokers. Table IA.9, panel D, in the Online Appendix presents the results. We show that both female coverage variables are positively and significantly associated with corporate E&S performance. In addition, we employ a t-test of differences between the two coefficients, and the p-value (>0.1) of the t-test indicates that the coefficient on *N_female_Top10* is not significantly different from that on *N_female_non-Top10*. This analysis suggests that our main findings are not likely driven by different broker cultures. Table IA.9, panel E, shows that our main findings remain controlling for a firm's socially responsible investment (SRI) fund ownership (Heath et al. 2023). This finding helps address the concern that our main finding is due to the monitoring of E&S-conscious investors.

[13] We thank an anonymous referee for making this suggestion.

[14] Following Jiang et al. (2016), we tried to use analysts' political contributions across all election cycles to capture their political leanings. We ended up with information on analysts' political leanings for 744 analysts over the period 2004–2020, whereas Jiang et al. (2016) were able to obtain the same information for 673 analysts over their sample period of 1993–2006. Unfortunately, this sample is too small for our regression analysis.

[15] We thank two anonymous referees for making this suggestion.

[16] According to I/B/E/S, recommendation stops because "an estimator places a stock on a restricted list due to an underwriting relationship, an analyst is leaving a firm, or the estimator no longer covers the company." If a recommendation is not updated or confirmed for more than 180 days, the recommendation is stopped. According to I/B/E/S, an analyst stops making EPS forecasts because "a merger between companies occurred, or an analyst stopped working for a firm, etc." If an estimate is not updated or confirmed for more than 210 days, the estimate is stopped.

[17] In theory, the event date should be a broker's exit date. In practice, broker closure dates (month) from Factiva and the FINRA BrokerCheck database do not always correspond with broker exit dates (month) from the I/B/E/S file because the completion of a broker's closure might take several months. Because there is no easy way of reconciling these event dates when they differ, we follow prior studies (see, e.g., Kelly and Ljungqvist 2012, Derrien and Kecskés 2013) and use a six-month "event period" (denoted t) centered around a broker's closure date.

[18] This last step is very important in obtaining a clean and precise sample for our DID analysis, because the number of analysts covering a firm was affected for various reasons. For example, LST Ltd. (ticker: "LST") was covered by a male analyst from Lehman Brothers in 2008, and that analyst no longer covered the firm afterwards. However, LST Ltd. was covered by 12 male analysts in 2007, 13 male analysts in 2008, and still 13 male analysts in 2009, indicating that a new male analyst from another broker started covering the firm in 2009. LST Ltd. did not experience a drop in male analyst coverage from 2007 to 2009, even though it had a male analyst from an exited broker in 2008. In another example, Kmart (ticker: "KMRT") was covered by a female analyst from Lehman Brothers in 2008, and similarly, that analyst no longer covered Kmart afterwards. Meanwhile, Kmart was covered by two female analysts in 2007, two female analysts in 2008, and one female analyst in 2009, meaning that it indeed suffered a drop in female analyst coverage because of a broker closure event. We keep those observations only if a firm was covered by a female (male) analyst from an exited broker, and the total number of female (male) analysts covering the firm decreases between the year before a closure event and the year after.

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

[20] In terms of economic significance, using column (1) as an example, the E&S performance of the treated firms (with a drop in female analyst coverage because of broker closures) decreases by 29.6% (0.138/0.466) relative to the mean compared with that of the matched control firms (without experiencing a drop in female analyst coverage but a drop in male analyst coverage). Given the very small but clean treated and control samples employed in our study, the economic magnitude of the effect should be interpreted with care.

[21] Although we acknowledge the criticisms by Loughran and McDonald (2014) regarding the use of traditional readability metrics for business texts such as 10-Ks, our analysis represents a more targeted and informative application. Rather than analyzing entire documents, we focus on specific E&S-related passages within analyst reports. Our objective is not to assess absolute readability but to examine relative differences in communication style between female and male analysts when discussing these E&S issues. As such, these metrics serve as useful proxies for stylistic differences in communication effectiveness.

[22] Table IA.11 shows that there are no significant gender differences in tones used by male and female analysts when discussing E&S issues during calls or in reports.

[23] In untabulated analysis, we find no significant associations between a firm's E&S incidents and female analysts changing target prices or earnings forecasts.

[24] For this analysis, we remove 1,301,826 reports due to companies with multiple reports, 128,440 reports due to companies issuing corporate announcements (from the Capital IQ Key Development database), in the CAR window.

[25] The 20.4-basis-point decrease is calculated from 0.204×100, and the \$22.8 million decrease in market capitalization is calculated from $0.204\% \times \$11.2$ billion, where \$11.2 billion is the sample average market capitalization in this analysis.

References

Adams RB, Funk P (2012) Beyond the glass ceiling: Does gender matter? *Management Sci.* 58(2):219–235.

Berg F, Kölbel JF, Rigobon R (2022) Aggregate confusion: The divergence of ESG ratings. *Rev. Finance* 26(6):1315–1344.

Berry WD, Ringquist EJ, Fording RC, Hanson RL (1998) Measuring citizen and government ideology in the American States, 1960-93. *Amer. J. Political Sci.* 42(1):327–348.

Bertrand M (2011) New perspectives on gender. Ashenfelter O, Card D, eds. *Handbook of Labor Economics* (Elsevier, Amsterdam), 1543–1590.

Beutel AM, Marini MM (1995) Gender and values. *Amer. Sociol. Rev.* 60(3):436–448.

Bolton P, Kacperczyk M (2021) Do investors care about carbon risk? *J. Financial Econom.* 142(2):517–549.

Boyd RL, Ashokkumar A, Seraj S, Pennebaker JW (2022) The development and psychometric properties of LIWC-22. Working paper, University of Texas at Austin, Austin.

Bradley D, Mao CX, Zhang C (2022) Does analyst coverage affect workplace safety? *Management Sci.* 68(5):3464–3487.

Cen L, Chen J, Dasgupta S, Ragunathan V (2021) Do analysts and their employers value access to management? Evidence from earnings conference call participation. *J. Financial Quant. Anal.* 56(3):745–787.

Chen T, Dong H, Lin C (2020) Institutional shareholders and corporate social responsibility. *J. Financial Econom.* 135(2):483–504.

Chen T, Harford J, Lin C (2015) Do analysts matter for governance? Evidence from natural experiments. *J. Financial Econom.* 115(2):383–410.

Comprix J, Lopatta K, Tideman SA (2022) The role of gender in the aggressive questioning of CEOs during earnings conference calls. *Accounting Rev.* 97(7):79–107.

Cormack CV, Grossman MR (2014) Evaluation of machine-learning protocols for technology-assisted review in electronic discovery. Geva S, Trotman A, Bruza P, Sitbon L, Scholer F, eds. *Proc. 37th Internat. ACM SIGIR Conf.* (Association for Computing Machinery, New York), 153–162.

Croson R, Gneezy U (2009) Gender differences in preferences. *J. Econom. Lit.* 47(2):448–474.

Derrien F, Kecskés A (2013) The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. *J. Finance* 68(4):1407–1440.

Devlin J, Chang M, Lee K, Toutanovam K (2019) BERT: Pre-training of deep bidirectional transformers for language understanding. Burstein J, Doran C, Solorio T, eds. *Proc. 2019 Conf. North American Chapter Assoc. Comput. Linguistics Human Language Technologies*, vol. 1 (Association for Computational Linguistics, Kerrville, TX), 4171–4186.

Di Giuli A, Kostovetsky L (2014) Are red or blue companies more likely to go green? Politics and corporate social responsibility. *J. Financial Econom.* 111(1):158–180.

Dyck A, Lins KV, Roth L, Wagner HF (2019) Do institutional investors drive corporate social responsibility? International evidence. *J. Financial Econom.* 131(3):693–714.

Ferrell A, Liang H, Renneboog L (2016) Socially responsible firms. *J. Financial Econom.* 122(2):585–606.

Gormley TA, Matsa DA (2014) Common errors: How to (and not to) control for unobserved heterogeneity. *Rev. Financial Stud.* 27(2):617–661.

Griffin D, Li K, Xu T (2021) Board gender diversity, corporate innovation, and firm value: International evidence. *J. Financial Quant. Anal.* 56(1):123–154.

Griffin PA, Lont DH, Sun EY (2017) The relevance to investors of greenhouse gas emission disclosures. *Contemporary Accounting Res.* 34(2):1265–1297.

Griffin D, Guedhami O, Li K, Lu G (2021) National culture and the value implications of corporate environmental and social performance. *J. Corp. Finance* 71(1):102–123.

Guo B, Pérez-Castrillo D, Toldrà-Simats A (2019) Firms' innovation strategy under the shadow of analyst coverage. *J. Financial Econom.* 131(2):456–483.

Harford J, Jiang F, Wang R, Xie F (2019) Analyst career concerns, effort allocation, and firms' information environment. *Rev. Financial Stud.* 32(6):2179–2224.

He J, Tian X (2013) The dark side of analyst coverage: The case of innovation. *J. Financial Econom.* 109(3):856–878.

Heath D, Macciocchi D, Michaely R, Ringgenberg MC (2023) Does socially responsible investing change firm behavior? *Rev. Finance* 27(6):2057–2083.

Hong H, Kacperczyk M (2010) Competition and bias. *Quart. J. Econom.* 125(4):1683–1725.

Hsu P, Li K, Pan Y (2025) The eco gender gap in boardrooms. *Management Sci.*, ePub ahead of print December 4, https://doi.org/10.1287/mnsc.2024.07730.

Huang J, Kisgen DJ (2013) Gender and corporate finance: Are male executives overconfident relative to female executives? *J. Financial Econom.* 108(3):822–839.

Huang AH, Wang H, Yang Y (2023) FinBERT: A large language model approach to extracting information from financial text. *Contemporary Accounting Res.* 40(2):806–841.

Huang AH, Zang AY, Zheng R (2014) Evidence on the information content of text in analyst reports. *Accounting Rev.* 89(6): 2151–2180.

Huang AH, Lehavy R, Zang AY, Zheng R (2018) Analyst information discovery and interpretation roles: A topic modeling approach. *Management Sci.* 64(6):2833–2855.

Irani RM, Oesch D (2013) Monitoring and corporate disclosure: Evidence from a natural experiment. *J. Financial Econom.* 109(2): 398–418.

Jiang D, Kumar A, Law KKF (2016) Political contributions and analyst behavior. *Rev. Accounting Stud.* 21(1):37–88.

Jing C, Keasey K, Lim I, Xu B (2023) Analyst coverage and corporate environmental policies. *J. Financial Quant. Anal.* 59(4): 1586–1619.

Kaufmann KM, Petrocik JR (1999) The changing politics of American men: Understanding the sources of the gender gap. *Amer. J. Political Sci.* 43(3):864–887.

Kelly B, Ljungqvist A (2012) Testing asymmetric-information asset pricing models. *Rev. Financial Stud.* 25(5):1366–1413.

Kölbel JF, Leippold M, Rillaerts J, Wang Q (2022) Ask BERT: How regulatory disclosure of transition and physical climate risks affects the CDS term structure. *J. Financial Econom.* 22(1):1–40.

Kumar A (2010) Self-selection and the forecasting abilities of female equity analysts. *J. Accounting Res.* 48(2):393–435.

Levi M, Li K, Zhang F (2014) Director gender and mergers and acquisitions. *J. Corporate Finance* 28(1):185–200.

Levi M, Li K, Zhang F (2015) Are women more likely to seek advice than men? Evidence from the boardroom. *J. Risk Financial Management* 8(1):127–149.

Li K, Mai F, Shen R, Yan X (2021) Measuring corporate culture using machine learning. *Rev. Financial Stud.* 34(7):3265–3315.

Li K, Peng R, Shen R, Wong G (2025) Gender, competition, and performance: International evidence. *J. Financial Quant. Anal.* 60(4): 1686–1726.

Li Q, Shan H, Tang Y, Yao V (2024) Corporate climate risk: Measurements and responses. *Rev. Financial Stud.* 37(6):1778–1830.

Loughran T, McDonald B (2014) Measuring readability in financial disclosures. *J. Finance* 69(4):1643–1671.

Matsa DA, Miller AR (2013) A female style in corporate leadership? Evidence from quotas. *Amer. Econom. Rev. Appl. Econom.* 5(3): 136–169.

Roberts ME, Stewart BM, Tingley D, Lucas C, Leder-Luis J, Kushner Gadarian S, Albertson B, Rand DG (2014) Structural topic models for open-ended survey responses. *Amer. J. Political Sci.* 58(4): 1064–1082.

Sautner Z, van Lent L, Vilkov G, Zhang R (2023) Firm-level climate change exposure. *J. Finance* 78(3):1449–1498.

Schwartz SH, Rubel T (2005) Sex differences in value priorities: Cross-cultural and multimethod studies. *J. Pers. Soc. Psychol.* 89(6):1010–1028.

Tate G, Yang L (2015) Female leadership and gender equity: Evidence from plant closure. *J. Financial Econom.* 117(1):77–97.

Tausczik YR, Pennebaker JW (2010) The psychological meaning of words: LIWC and computerized text analysis methods. *J. Lang. Soc. Psychol.* 29(1):24–54.

Whang S, Roh Y, Song H, Lee J (2023) Data collection and quality challenges in deep learning: A data-centric AI perspective. *VLDB J.* 32(4):791–813.

Yu F (2008) Analyst coverage and earnings management. *J. Financial. Econom.* 88(2):245–271.

Zha D, Bhat Z, Lai K, Yang F, Hu X (2023) Data-centric AI: Perspectives and challenges. Shekhar S, Xiong H, Zhou X, eds. *Proc. 2023 SIAM Internat. Conf. Data Mining (SDM)* (Society for Industrial and Applied Mathematics, Philadelphia), 945–948.