

The value of values: Does focusing on sustainability provide a competitive advantage in forecasting earnings?*

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Abstract

We identify sustainability-focused analysts using recent advances in machine learning combined with conference call transcript data. Sustainability-focused analysts issue more accurate earnings forecasts, and the stock market reacts more strongly to their revisions. Analysts focus on sustainability when they are more experienced and the firm has low analyst coverage. Our results provide new evidence on the determinants and consequences of analysts' sustainability focus. Moreover, they suggest that far from being an inefficient use of time and resources, focusing on sustainability provides a competitive advantage in one of the most pivotal steps in valuation - forecasting earnings.

Keywords: Analyst Forecast Accuracy; Sustainability; Machine Learning; Natural Language Processing; BERT

1 Introduction

In her 2023 Presidential Address to the American Finance Association, Laura Starks highlights that there is significant debate on whether incorporating sustainability issues such as ESG into the investment process provides market participants with a competitive edge (‘value’) or leads them to sacrifice performance arising from non-pecuniary preferences (‘values’) (Starks, 2023). We address the debate by providing novel evidence on whether focusing on sustainability provides a competitive advantage in one of the most pivotal steps in valuation: forecasting earnings. We use the setting of equity analysts because they are forecasting specialists who acquire and process both “soft” and “hard” information about firms. Specifically, we study whether an analyst’s forecast accuracy relative to her peers improves when she focuses on sustainability for a covered firm. We broaden our analysis of whether focusing on sustainability provides an advantage in valuation by studying the short-window stock market reaction to earnings forecast revisions as well as the determinants of an analyst’s decision to focus on sustainability for a covered firm.

We introduce a novel method to identify sustainability-focused analysts using recent advances in machine learning and data on analysts’ questions during conference calls. A rapidly growing literature uses conference call data to glean value-relevant information about firms (e.g., Sautner et al., 2023; Hassan et al., 2019, 2023a,b; Chen et al., 2018). Further, the questions asked by analysts on conference calls reveal the topics they are actively focused on for a particular firm. Because analysts face limited opportunities to communicate with management, the discussion topics they raise during Q&A indicate the issues they are keenly interested in and deem important for their personal understanding of the firm. Consistent with analysts engaging meaningfully with managers, Matsumoto et al. (2011) find that the Q&A portion is the primary source of information arising from conference calls.

Ex-ante, there are at least three reasons why analysts who focus on sustainability issues (e.g. ESG) may generate inferior earning forecasts. First, sustainability may be a distraction

when forecasting earnings if it does not play a significant role in shaping corporate profitability or if the payoffs related to sustainability activities are sufficiently risky and uncertain (e.g. [Goldstein et al., 2022](#)). Second, prior work suggests that sustainability information itself is difficult to analyze and interpret and also susceptible to greenwashing (e.g., [Christensen et al., 2022](#); [Berg et al., 2022](#); [Fiechter et al., 2022](#)). If it is sufficiently costly to process such information when forecasting earnings, focusing on sustainability issues will not be a fruitful use of an analyst’s attention and effort. Third, even if sustainability issues are useful in forecasting earnings, asking managers about these topics during the conference call could simply signal that the asking analyst does not adequately understand these issues.

On the other hand, a burgeoning empirical and theoretical literature discussed in Section 2.2 (e.g., [Edmans, 2011, 2021, 2022](#); [Green et al., 2019](#); [Aghamolla and An, 2021](#); [Larcker et al., 2007](#); [Pástor et al., 2021](#); [Albuquerque et al., 2019](#); [Reboredo and Ugolini, 2022](#); [Friedman et al., 2022](#); [Pedersen et al., 2021](#)) posits that corporate profits are affected by sustainability-related issues including a company’s relationships with its employees, environment, communities, customers and other stakeholders. Under this view, an analyst can generate more precise expectations of future earnings for a covered firm if she expends the effort needed to understand and integrate the payoffs from the firm’s sustainability activities into her earnings forecasts.

We use a pre-trained machine learning model based on Google’s Bidirectional Encoder Representations from Transformers (BERT) to classify whether an analyst question is sustainability-focused by determining whether it relates to one of the sustainability dimensions defined by the Sustainability Accounting Standards Board (SASB). BERT is one of the most powerful natural language processing (NLP) algorithms at the time of this writing and has shown superior performance in language tasks used in the finance and accounting literature such as text classification and sentiment analysis (e.g. [Siano and Wysocki, 2021](#); [Frankel et al., 2022](#); [Huang et al., 2022](#)).

We classify an analyst as sustainability-focused for a given firm-year if the analyst asks at least one sustainability-focused question during one of the firm’s conference calls in the past year. We measure sustainability focus at the analyst-firm-year level for several reasons. First, analysts face limited time, energy and resources (e.g. Harford et al., 2019; Hirshleifer et al., 2019) and likely choose whether or not to focus on sustainability for a firm depending on the unique cost-benefit trade-off faced by the analyst at that time.¹ Second, sustainability issues are dynamic and their importance for a given firm can change over time. For example, Serafeim and Yoon (2022b) highlight that the “the relationship between different ESG issues and financial performance is likely to vary over time...and with different intensity across companies”. Third, our approach avoids lookahead bias since it uses strictly ex-ante information. Fourth, it enables us to conduct both within-analyst as well as within-analyst-firm tests and thereby control for a variety of unobservable heterogeneity.

We begin by providing new descriptive evidence on the extent to which analysts focus on sustainability. On average, analysts focus on sustainability for 20% of the firms they cover per year. 47% of all conference calls contain at least one sustainability-focused question, indicating that sustainability is important for many firms. Further, 33% of analysts who cover a given firm focus on sustainability issues for that firm per year. Our finding that analysts routinely focus on sustainability is consistent with survey evidence that many finance professionals use ESG information in investment decision-making (Amel-Zadeh and Serafeim, 2018; Bancel, Glavas, and Karolyi, 2023).

Our main result is that when an analyst focuses on sustainability for a covered firm, her earnings forecast accuracy improves relative to other analysts covering the same firm. Our finding that focusing on sustainability provides a forecasting advantage is robust to analyst-, firm- and analyst-firm fixed effects as well as controlling for the number and length of questions asked by an analyst. Our results also continue to hold after restricting the

¹As such, we do not calculate an analyst-year level measure of sustainability-focus.

sample to analysts participating in the conference call, who have been suggested to issue more favorable and accurate forecasts (e.g. [Mayew, 2008](#); [Mayew et al., 2013](#)).

We conduct a series of tests to shed light on the mechanism through which sustainability focus affects analysts' forecasts. If focusing on sustainability provides a forecasting advantage, we expect this advantage to grow when an analyst focuses on the financial impact of firms' sustainability activities. We test this in two ways. First, we examine if the advantage enjoyed by a sustainability-focused analyst increases when she focuses on material sustainability issues. For these tests, we exploit the materiality maps developed by the Sustainability Accounting Standards Board (SASB), which allow us to identify sustainability issues that are *both* financially material and also have a significant impact on the environment and society (i.e. these sustainability issues have "double materiality"). Second, we examine if an analyst's forecast accuracy improves when she focuses on mapping the financial impact of sustainability into firm fundamentals. Accordingly, we refine our classification based on whether an analyst's sustainability-focused question includes financial terms such as "revenues", "expenses", "earnings", "profits" or "losses".

We find that 38% (23%) of all sustainability-focused analysts focus on material sustainability (financial impact-related sustainability) issues. Moreover, focusing on such issues further improves the forecast accuracy of sustainability analysts. Regarding economic magnitude, the improvement in accuracy when an analyst focuses on sustainability for a covered firm is equivalent to about 6.5% of the standard deviation of forecast accuracy in our sample. For analysts who focus on material (financial impact-related) sustainability issues, this effect increases to 7.6% (8%) of the standard deviation of forecast accuracy in our sample.

Third, given the multifaceted nature of sustainability issues, we use the SASB-defined dimensions of sustainability to examine whether analyst forecast accuracy is affected by the specific category of sustainability on which an analyst focuses. We draw on the five sustainability dimensions defined by SASB: Environment, Social Capital, Human Capital, Business Model & Innovation, and Leadership & Governance. We find that forecast accuracy

improves significantly when analysts focus on each of these dimensions, suggesting that our results apply broadly and are not driven by a minority of sustainability categories.

Fourth, we examine the short-window three-day stock return response to earnings forecast revisions by sustainability-focused analysts. We find that the sensitivity of stock returns to analyst forecast revisions significantly increases when an analyst focuses on sustainability for a covered stock. In fact, the sensitivity of returns to analyst revisions almost doubles when an analyst focuses on material sustainability issues. This suggests that stock market investors place greater importance on forecasts by sustainability-focused analysts.

Fifth, we examine whether the competitive edge enjoyed by sustainability-focused analysts is affected by analyst and firm characteristics. Consistent with a learning curve associated with understanding how sustainability issues relate to firm performance, we find that more experienced analysts reap greater improvements in accuracy when they focus on sustainability compared to less experienced analysts. We also find that focusing on sustainability provides a greater forecasting advantage in small firms and high market-to-book firms, indicating a heightened competitive edge from focusing on sustainability in firms with greater information asymmetry.

Sixth, we investigate the horizon over which focusing on sustainability delivers a forecasting advantage. Consistent with prior studies (e.g., O'Brien, 1990; Sinha et al., 1997; Clement, 1999; Clement and Tse, 2005; Mayew et al., 2013), our results focus on one-year-ahead EPS forecasts. If the implications of sustainability for firm performance materialize over long horizons, we expect that the forecasting advantage enjoyed by sustainability-focused analysts also manifests for longer term earnings forecasts. Consistent with this, we find that sustainability-focused analysts issue more accurate two-year-ahead EPS forecasts compared to other analysts covering the same firm.

We also probe the determinants of sustainability focus. We document that analysts are more likely to focus on sustainability when they are more experienced, which dovetails with our earlier finding that experienced analysts benefit more from focusing on sustainability.

Analysts are also more likely to focus on sustainability issues among firms with low analyst coverage and smaller market capitalization, consistent with them focusing on sustainability when there is greater information asymmetry.

A potential methodological concern in identifying sustainability-focused analysts is that all analysts might benefit equally from questions asked by sustainability-focused analysts because conference calls are public information and observable by all analysts. However, this concern is mitigated for several reasons. First, there is significant variation in analysts' ability to interpret and impound sustainability information. For example, we find that less experienced analysts reap lower benefits in terms of forecast accuracy when they focus on sustainability compared to more experienced analysts. Moreover, even ESG experts disagree on how to process ESG information (e.g., [Berg et al., 2022](#); [Christensen et al., 2022](#)). Processing sustainability information and mapping its implications for future cash flows is likely to be challenging and costly for equity analysts, and the asking analyst is likely better able to do this than other analysts.

Further, asking a sustainability-related question is simply a signal that an analyst is focused on sustainability, and their question may not completely reveal all their private information. Moreover, the information gleaned from management by the asking analyst can allow her to complete her "information mosaic" and heighten her information advantage relative to other analysts. The notion of analysts completing an information mosaic has found support in court. For example, in *Elkind v. Liggett & Myers, Inc* (2d Cir. 1980), the court stated that "[a] skilled analyst with knowledge of the company and the industry may piece seemingly inconsequential data together with public information into a mosaic which reveals material nonpublic information.". Indeed, theoretical and empirical work shows that public disclosure can *increase* information asymmetry between market participants, especially when the information is costly to process (e.g., [Cheynel and Levine, 2020](#); [Bertomeu et al., 2011](#); [Coller and Yohn, 1997](#); [Krinsky and Lee, 1996](#)). Consistent with this, [Mayew \(2008\)](#) points out that although management's answer to a question is observable to all analysts, it can still

yield uniquely valuable private information for the asking analyst once it is conditioned on her existing unique information set. Finally, if all analysts benefit equally from any information revealed by sustainability-focused analysts, it would not explain our empirical finding that forecasts by sustainability-focused analysts (particularly those focused on material sustainability issues) are significantly more accurate and evoke stronger market reactions than forecasts by non-sustainability-focused analysts covering the same firm.

We highlight that our fixed effects structure enables us to overcome an identification challenge commonly faced in the sustainability literature. This literature is often constrained to using firm-level research designs that make it difficult to be certain that the results are not driven by unobservable firm-level characteristics that are correlated with the firm's sustainability-related disclosure or performance. Our within-firm design mitigates such concerns. Further, our use of analyst fixed effects enables us to isolate within-analyst variation and control for overall analyst characteristics such as reputation and ability. As a further test, we add fixed effects for each analyst-firm pair to isolate within-analyst-firm variation and control for factors like analyst-management relationships and endogenous analyst-firm matching. The robustness of our results to analyst-firm pair effects is especially notable because we are holding the pairing constant to examine the accuracy of the same analyst covering the same firm depending on whether or not she focuses on sustainability at that time for that firm. As such, we are able to provide unique evidence on the competitive edge enjoyed by individual market participants when they focus on sustainability, as well as the mechanism associated with this competitive edge.

Our paper makes several contributions. First, we contribute to the ongoing debate on the role of sustainability and ESG issues in investing. While some regard the inclusion of these issues in valuation and investment processes as a harmless distraction (at best) or an inefficient use of valuable resources (at worst), others regard it as an essential, highly value-relevant step. We provide some of the first evidence that focusing on sustainability provides a competitive advantage in one of the most pivotal steps in valuation: forecasting earnings.

Notably, we depart in several ways from influential work by [Dhaliwal et al. \(2012\)](#), who document that at the firm level, voluntary disclosure of a CSR report by a firm is associated with smaller average analyst forecast errors. Specifically, they do not examine the cross-section of analysts covering the same firm to shed light on whether sustainability-focused analysts have a competitive edge in forecasting compared to non-sustainability-focused analysts. In fact, we find that controlling for the disclosure of a voluntary sustainability report by a firm does not significantly alter the competitive advantage associated with focusing on sustainability. We also stress that our study explicitly examines many important topics unexplored by prior work (e.g. [Dhaliwal et al., 2012](#); [Muslu et al., 2019](#)) including the stock market reaction to revisions by sustainability-focused analysts, the determinants of analysts' sustainability focus, and whether experience and focusing on material sustainability issues enhances the competitive edge of sustainability-focused analysts.

Second, we contribute to the literature by examining one of the most important information agents in capital markets - equity analysts. While a large literature studies the properties of analysts' outputs and it is well-accepted that analysts engage in costly information acquisition and processing ([Bradshaw, 2011](#); [Brown et al., 2015](#); [Lee et al., 2023](#)), a persistent difficulty faced by researchers is their inability to observe the specific factors and inputs that shape analysts' forecasts. We shed light on this by first constructing a new measure of analysts' sustainability focus and providing descriptive evidence on the extent to which analysts focus on sustainability. Our finding that analysts frequently focus on sustainability comports with both recent survey evidence by [Bancel, Glavas, and Karolyi \(2023\)](#) that 41.6% of finance executives integrate ESG into earnings when implementing a discounted cash flow (DCF)-style valuation.

Third, we make a methodological contribution by introducing a novel machine learning-based technique to measure sustainability content. This methodology is superior to other text-based techniques (e.g., bag-of-words methods) used in prior studies (e.g., [Bochkay et al., 2021](#); [Hail et al., 2021](#)), because unlike bag-of-words methods, the BERT model generates

context-specific embeddings for each word. Computational linguistic studies show that large language models such as BERT can substantially outperform other NLP algorithms in many NLP tasks such as language translation, named entity recognition, and text classification (Devlin et al., 2018). While we examine the content of analysts’ questions during conference calls, this methodology can be used to detect sustainability content in other settings such as news articles, corporate disclosures, and social media. In this regard, our study is related to recent studies by Giglio et al. (2023), who use a BERT-based model to classify the sentiment of biodiversity-related articles, and Huang et al. (2022), who fine-tune their pre-trained FinBERT model to classify firms’ ESG discussions in voluntary ESG reports and the management discussion and analysis (MD&A) section of 10-K filings. While Huang et al. (2022) only use three broad categories (Environmental, Social, and Governance) for their ESG classification task, the ESG-BERT model we use classifies text based on the comprehensive sustainability framework created by the Sustainability Accounting Standards Board (SASB) which covers almost two dozen ESG issues across five ESG dimensions using industry-specific mappings. As such, our methodology not only draws on a richer classification scheme but also has the advantage of enabling us to identify sustainability topics that are material to each firm.

This paper is organized as follows. In Section 2, we provide background for our study. In Section 3, we provide a detailed description of our sample and data procedures. Section 4 discusses our research design and results. Section 5 concludes.

2 Background

Interest in the role of sustainability and ESG in firm valuation has accelerated among practitioners in recent years. According to a recent Bloomberg Intelligence report on ESG investing, global ESG assets may surpass \$50 trillion by 2025 (Henze and Boyd, 2022). Similarly, academic research examining the role of sustainability and ESG in investing is rapidly growing (e.g., Dechow, 2023; Khan et al., 2016; Ryou et al., 2022). However, policymakers

and capital market participants are divided on whether the consideration of sustainability issues actually provides capital market participants with a competitive edge (e.g. [Starks, 2023](#); [Giglio et al., 2023](#); [Ackerman and Wise, 2023](#)). Since analysts are key financial market information intermediaries who specialize in forecasting earnings, we examine whether focusing on sustainability impacts analysts' relative forecast accuracy and the market reaction to their forecasts. In the following subsections, we provide background relevant to our study.

2.1 Prior work on Analysts and Conference Calls

Because equity analysts specialize in forecasting and valuation, a vast body of work focuses on the investment value of analyst research (e.g., [Joos et al., 2016](#); [De Franco et al., 2015](#); [Cheng, 2005](#); [Bradshaw et al., 2013](#)). It is also well-accepted that the accuracy of analysts' earnings forecasts is of consequence to analysts' careers since analysts are evaluated based on their forecast accuracy relative to their peers and lower forecast accuracy is associated with higher analyst turnover ([Brown et al., 2015](#); [Mikhail et al., 1999](#); [Groysberg et al., 2011](#)). In particular, a large body of literature examines the factors that impact analyst forecast accuracy, as it is a summary statistic capturing the quality of an analyst's research process and output. For example, [Hirshleifer et al. \(2019\)](#) document that decision fatigue adversely affects the accuracy of analysts' earnings forecasts, while [Ljungqvist et al. \(2007\)](#) document that the presence of institutional investors is associated with more accurate earnings forecasts and [Clement and Tse \(2005\)](#) find that analysts' bold forecasts are more accurate than their herding forecasts. [Li et al. \(2023\)](#) suggest that analysts with better social skills produce more accurate earnings forecasts, and [Han et al. \(2023\)](#) find that earnings forecasts by analysts who experienced a major climatic disaster become less accurate than those by unaffected analysts.

The enactment of Regulation Fair Disclosure (Reg FD) in October 2000 addressed concerns that conference calls encouraged selective disclosure by revealing new information to analysts privy to the call (e.g., [Levitt, 1998](#); [Chen et al., 2010](#)). In the post-Reg FD environ-

ment, conference calls must be publicly available, in the sense that all market participants can listen to the call or read the call transcript in real-time (Bushee et al., 2004).² Moreover, extant research has shown that conference calls increase the total information available about a firm (e.g., Frankel et al., 1999; Brown et al., 2004; Davis et al., 2015; Call et al., 2023) and thereby enhance analysts’ ability to forecast earnings (Bowen et al., 2002). Conference calls are incrementally informative to market participants because managers can voluntarily provide new information in the conference call in a less formal setting compared to regulatory filings while enjoying safe harbor protection with respect to legal liability (Allee et al., 2021). A rapidly growing literature uses the content of conference calls as a rich source of information about firms. Sautner et al. (2023) use conference call data to measure firms’ exposure to climate change, Hassan et al. (2023b) use such data to measure firms’ exposure to Brexit uncertainty, and Hassan et al. (2023a) use conference call data to measure spikes in perceived country risk.

Analysts play a key role in conference calls since they can query and engage with managers during the (Q&A) portion of the call (Rennekamp et al. (2022); Mayew et al. (2020)). Matsumoto et al. (2011) shed light on the informativeness of conference calls by examining the information content of the executive presentation portion versus the Q&A session separately and find that Q&A sessions are the primary source of information to capital markets arising from conference calls.

The higher information content of the Q&A portion of conference calls is attributed to analysts’ questions, which are driven by the topics that analysts are actively focused on and deem important for their personal understanding of the firm. As Mayew (2008) highlight, once analyst questions are conditioned on the asking analyst’s existing unique information set, the public answer, while heard by all analysts, can yield a unique information advantage for the analyst asking the question relative to other analysts. Specifically, the public information that is disseminated as a result of a manager’s response to an analyst’s

²Under Section 102 Rule 101 of Reg FD, issuers are required to provide an “adequate” advance notice publicly, that includes the date, time, subject matter, and call-in information for the conference call.

question complements the existing private information possessed by the analyst, rather than merely substituting for it (Kim and Verrecchia, 1997; Barron et al., 2002).

2.2 Analyst forecast accuracy and focus on sustainability

Ex-ante, there are at least three reasons why analysts who focus on sustainability issues during conference calls may generate earning forecasts that are of inferior quality. First, if sustainability issues do not play a significant role in firm profitability or the payoffs from sustainability activities are sufficiently risky and uncertain (e.g. Goldstein et al., 2022), focusing on sustainability may be an inefficient use of analysts' time and resources. Second, prior work suggests that ESG information is difficult to interpret and analyze, even for experts (Christensen et al., 2022; Berg et al., 2022; Griffin et al., 2020; Moroney and Trotman, 2016). An additional challenge in interpreting and processing sustainability-related data (e.g. ESG data) arises from greenwashing, which broadly refers to activities aimed at increasing firms' ESG reputation beyond their actual ESG achievements (e.g. Fiechter et al., 2022; Pinnuck et al., 2021).

Consistent with significant subjectivity and lack of consensus in the processing and integration of sustainability information, Berg et al. (2022) document significant rating divergence among six prominent ESG rating agencies, and Christensen et al. (2022) find that greater ESG disclosure actually leads to greater ESG disagreement among ESG rating agencies. Prior work suggests that the quality of analysts' forecasts suffers when analysts encounter information that is difficult to process (Plumlee, 2003; Blankespoor et al., 2020). If it is sufficiently costly to acquire, process, and integrate sustainability-related information when forecasting earnings, focusing on these issues will not be a fruitful use of an analyst's effort and attention. Third, asking about sustainability issues during the conference call could signal that the asking analyst does not adequately understand sustainability issues and/or their mapping to firm performance. For these reasons, analyst forecast accuracy may decline when an analyst focuses on sustainability.

On the other hand, a growing body of empirical and theoretical work posits that corporate profitability is affected by sustainability-related factors such as a company’s relationships with its employees, environment, communities, customers and other stakeholders. For example, [Khan et al. \(2016\)](#) find empirical evidence that material sustainability ratings predict changes in profitability. [Green et al. \(2019\)](#) find that changes in Glassdoor employer ratings forecast profitability, sales growth, earnings surprises and returns. [Reboredo and Ugolini \(2022\)](#) find that firms’ climate transition risk forecasts future profitability.³ [Larcker et al. \(2007\)](#) document that corporate governance factors forecast profitability. [Edmans \(2011\)](#) documents that firms with high employee satisfaction identified using the ‘100 Best Companies to work for in America’ list exhibit significantly more positive future earnings surprises, announcement returns and risk-adjusted returns than industry benchmarks. Findings such as these lead [Edmans \(2021\)](#) and [Edmans \(2022\)](#) to conclude that ESG is a critical driver of firm performance which should be taken into account by investors when valuing firms.

Numerous theoretical models also posit that a firm’s sustainability activities affect its profits. In the model of [Friedman et al. \(2022\)](#), the firm’s earnings are affected by its ESG efforts as well as other factors not related to ESG. The earnings implications of ESG efforts can include penalties, subsidies, physical and transition risk, as well as other investments in ESG. For example, an oil company might incorporate carbon capture and storage into its production process. This costly activity affects the firm’s profits. As such, ESG actions can have positive or negative implications for profitability. The model of [Aghamolla and An \(2021\)](#) features a firm manager who makes an investment in an ESG project which affects future earnings and the externalities produced by the firm. [Albuquerque et al. \(2019\)](#) model CSR as an investment which increases product differentiation and allows firms to benefit from higher profit margins. [Pástor et al. \(2021\)](#) show that a firm’s ESG characteristic affects expected earnings when managers can choose the firm’s operating capital and its ESG

³[Griffin et al. \(2017\)](#) and [Johnson et al. \(2020\)](#) suggest that firms’ emissions of greenhouse gas negatively impact firm value. More broadly, [Guiral et al. \(2020\)](#) suggest that CSR performance affects firms’ financial performance, while [Elliott et al. \(2017\)](#) suggest that the presentation of CSR information plays a role in investors’ investment decisions.

characteristic, and in the ESG-CAPM model of [Pedersen et al. \(2021\)](#), a firm’s expected earnings are affected by its ESG score.⁴

Prior work provides limited insight into whether considering sustainability issues helps or hurts an individual analyst’s forecast accuracy. [Dhaliwal et al. \(2012\)](#) and [Muslu et al. \(2019\)](#) use a global dataset to show that aggregate analyst forecast accuracy is positively associated with the issuance of stand-alone voluntary CSR reports and the quality of these disclosures. However, the analyses in these studies are conducted at the firm level, and thus do not shed light on whether the forecast accuracy of individual analysts changes relative to their peers when focusing on sustainability for the same covered firm. As such, these studies do not provide insight into whether analyzing CSR information provides individual analysts with a competitive advantage in forecasting. Moreover, we do not find that the disclosure of a voluntary sustainability report by a firm significantly alters the competitive advantage of sustainability-focused analysts. This is consistent with our findings (which relate to the cross-section of analyst forecast accuracy within each firm) being independent of [Dhaliwal et al. \(2012\)](#) and [Muslu et al. \(2019\)](#). Finally, we go beyond prior work such as [Dhaliwal et al. \(2012\)](#) and [Muslu et al. \(2019\)](#) by examining important issues such as the stock market reaction to earnings revisions by sustainability-focused analysts, the determinants of analysts’ sustainability focus, and whether cross-sectional factors affects the forecast accuracy of sustainability-focused analysts. For example, we demonstrate that a sustainability-focused analyst’s relative forecast accuracy improves even more when she focuses on sustainability issues that are both financially material and also have a significant impact on the environment and society. Further, our evidence suggests there is a learning curve associated with understanding how sustainability issues relate to future performance. As such, we contribute to the literature by shedding light on key topics that are unexplored by extant research.

[Park et al. \(2023\)](#) document that analysts’ outputs such as stock recommendations and EPS forecasts predict ESG incidents, consistent with analysts integrating ESG risks into their

⁴See Section 6.2 of [Pástor et al. \(2021\)](#) and Equation 20 of [Pedersen et al. \(2021\)](#)

research. However, they do not investigate whether focusing on ESG provides a competitive advantage to an individual analyst relative to her peers when forecasting earnings for the same firm. [Derrien et al. \(2022\)](#) document that analysts in developed European countries who react to ESG incidents exhibit better forecast accuracy. However, they fail to find such a result in the US. In our robustness tests we explicitly control for ESG incidents and find that our inferences are unchanged. As such, our results are not driven by ESG incidents. Moreover, they do not examine the stock market reaction to revisions by ESG-focused analysts, the determinants of ESG focus, nor the role of material ESG issues or analyst experience.⁵

3 Sample, Data Sources, and Variables

This section documents the data sources used in this study, the construction of the main variables, and summary statistics for the variables used in our analyses.

3.1 Sample and Data Sources

Consistent with prior studies (e.g., [O'Brien, 1990](#); [Sinha et al., 1997](#); [Clement, 1999](#); [Clement and Tse, 2005](#); [Mayew et al., 2013](#)), our sample focuses on analysts' latest one-year-ahead earnings forecasts that are within 365 days to 30 days before the actual earnings announcement.⁶ These data come from the I/B/E/S Detail History file for the period between 2008 and 2020. Our sample begins in 2008 because S&P CapitalIQ's conference call

⁵Other papers examining the firm-level relation between ESG and properties of analyst forecasts are as follows (notably, these papers do not examine the cross-section of analysts covering each firm to investigate if sustainability-focused analysts enjoy a competitive advantage in forecasting earnings for a covered firm): [Bernardi and Stark \(2018\)](#) examine data from South Africa and find that the level of ESG disclosures is a mediating variable in determining the effectiveness of integrated reporting using analyst forecast accuracy to evaluate investors' perceptions of the usefulness of integrated reporting. [Becchetti et al. \(2013\)](#) decompose CSR into four factors: accounting opacity, corporate governance, stakeholder risk and overinvestment. They document that all of these factors affect analysts' absolute EPS forecast errors and its standard deviation. [Orens and Lybaert \(2010\)](#) survey Belgian sell-side analysts and suggest that analysts who use more forward-looking information and more internal-structure information make more accurate forecasts. [Umar et al. \(2022\)](#) examine data from Brazil, Russia, India, China, and South Africa (BRICS) and find that ESG scores positively impact target price accuracy, and firms with higher ESG scores have lower forecast errors. [Schiemann and Tietmeyer \(2022\)](#) find that analyst forecast errors are generally higher for firms with higher exposure to ESG controversies.

⁶In Section 4.7, we also examine two-year-ahead earnings forecasts.

transcript data coverage was expanded in 2008. To construct our sample, we first eliminate observations where analysts cannot be identified, i.e., where analyst codes in the I/B/E/S database are missing or equal to zero. Next, we eliminate observations for which data on firm characteristics from Compustat and CRSP are missing. These screening criteria yield a sample of 272,096 analyst-firm-year observations, corresponding to 4,478 analysts issuing earnings forecasts for 3,999 unique firms. To measure analysts’ focus on sustainability issues, we use analyst transcripts from S&P CapitalIQ’s conference call transcript data. We follow the approach in Du et al. (2022) to create translation files between CapitalIQ’s conference call participants dataset and the I/B/E/S price targets and recommendation detail files.⁷

We then identify all questions asked by each analyst in conference calls occurring in the year before they issue their earnings forecast.⁸ Figure 1 depicts our research design for measuring the timing of analyst forecasts relative to the earnings announcement date, as well as the timing window to identify analyst questions focused on sustainability. We eliminate questions or comments that contain less than 10 words, as our manual review of a random sample of 50 of these transcripts revealed there is no meaningful content in these snippets.⁹ This process generates 1,581,482 analyst transcripts. Table 1 describes our sample selection procedure.

[Insert Figure 1 and Table 1 around here.]

On average, analysts focus on sustainability for 20% of the firms they cover, in a given year. 47% of all conference calls contain at least one sustainability-focused question, indicating that sustainability issues are important for many firms. On average, 33% of analysts who cover a firm focus on sustainability issues for that firm per year. Our finding that analysts regularly focus on sustainability is consistent with survey evidence that ESG information is

⁷The detailed process and translation files are available from Jared Flake and Mark Piorkowski’s GitHub repository (https://github.com/j4ffle/CapIQ_IBES_Match).

⁸In an untabulated robustness test, we find that our inferences are unchanged when we limit this period to one quarter.

⁹Some examples of these are: “All right. Take care. Thanks.”, “Okay. Go ahead. I’m sorry.”, and “Yes, that’s why I was asking.”

used by a significant fraction of finance professionals in investment decision-making (Amel-Zadeh and Serafeim, 2018; Bancel, Glavas, and Karolyi, 2023).

3.2 Measuring Analysts’ Focus on Sustainability Issues

We take a novel approach to measure analysts’ focus on sustainability issues by identifying the questions they ask in conference calls which relate to sustainability.¹⁰ As discussed in Section 2, this approach relies on three main findings from prior research. First, Matsumoto et al. (2011) establish that due to the involvement of analysts, the question and answer (Q&A) portion of earnings conference call has more information content than the presentation portion. Second, Mayew et al. (2013) suggest that analyst questions during conference calls are driven by analysts’ active interest in specific issues, and the information acquired by asking a question can complement the analysts’ existing information set and yield new valuable private information. Third, it is unlikely that analysts raise “softball” questions, since analysts face limited opportunities to engage with managers and raising irrelevant or low quality questions in a conference call that is publicly disseminated can have negative reputation and career consequences for analysts.

3.2.1 Natural Language Processing Algorithm

To capture analyst questions relating to sustainability, we use a pre-trained machine learning model that is trained based on Google’s Bidirectional Encoder Representations from Transformers (BERT) methodology. At the time of this writing, BERT is one of the most powerful NLP algorithms relative to the size, time and resources required to train

¹⁰A potential concern is that multiple analysts have the same question as the asking analyst. This concern is mitigated for three reasons. First, if this were the case, then questions about sustainability may appear earlier in the Q&A portion of the conference call. However, in untabulated tests, we do not find a significant difference in the order of sustainability questions and other questions. Further, prior work by Cen et al. (2021) suggests that managers determine the order in which questions are asked. Consistent with this a survey of 610 IROs by Brown et al. (2019) found that the majority actively manage the order in which callers are selected. Second, we use all conference calls over the past year to identify sustainability-focused analysts. Thus, our identification is not based on just a single conference call episode; rather, we allow multiple events in which analysts could ask questions from managers. Third, it would bias against finding a significant treatment effect for sustainability-focused analysts, since some sustainability-focused analysts would be incorrectly classified as non-sustainability-focused analysts.

or obtain inferences from a pre-trained model. Historically, many NLP algorithms with a bag-of-words structure have been used in the accounting and finance literature to parse large amounts of unstructured text in order to measure disclosure sentiment, readability, quality, and quantity; to compare disclosures and determine similarities or differences; to identify forward-looking information; and to detect themes from annual reports (Bochkay et al., 2023).¹¹ However, these algorithms mostly ignore context and instead analyze the text as a collection of individual words treated independently without taking grammar or word order into account, leading to limited accuracy in many contexts (e.g., Bochkay et al., 2023). With recent advances in machine learning and deep learning, large language models (LLMs) such as BERT have delivered superior performance in many language tasks, such as text classification and sentiment analysis that are often used in the accounting and finance literature (Siano and Wysocki, 2021; Frankel et al., 2022; Huang et al., 2022).¹² Training an LLM usually includes two steps: pre-training and fine-tuning. During pre-training, BERT learns semantic and syntactic information from a large corpus of unlabeled text. During fine-tuning, BERT learns downstream NLP tasks, such as text classification.

We use a BERT model which is first pre-trained on unstructured ESG-related text from 4,000 articles and sustainability reports to create initial token, sentence, and positional embeddings for the ESG context. The reported accuracy of this model for next sentence prediction and masked language modelling tasks are 100% and 98%, respectively.¹³ Next, the pre-trained model is fine-tuned for the ESG topic classification task using 11,000 ESG-related articles from Dow Jones that are classified using the SASB’s sustainability standards into 24 sustainability categories across five sustainability dimensions: Environment, Social

¹¹See Huang et al. (2022) for a complete list of algorithms with a bag-of-words structure.

¹²Some other recent LLMs that have shown promising results on NLP tasks such as text classification, question answering, and next sentence prediction include Open AI’s GPT-4, and Microsoft and NVIDIA’s MT-NLG.

¹³The accuracy of machine learning models is calculated as the ratio of the number of correct predictions divided by total number of predictions ($Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative}$).

Capital, Human Capital, Business Model & Innovation, and Leadership & Governance.^{14,15} After the fine-tuning process, the model’s reported F1-score on the hold-out test sample is 90%, which is a significant improvement compared to the benchmark model’s F1-score of 0.79 using the “BERT-BASE” off-the-shelf model that was trained on articles from Wikipedia and Google Books corpus.^{16,17}

This NLP model returns the sustainability label that best describes the text along with the confidence level of that label, ranging from 0% to 100%. The confidence level indicates how likely the text relates to the predicted sustainability category. We set the confidence level threshold at 80% to identify analysts’ sustainability questions.¹⁸ Following this procedure, we identify 102,113 sustainability-related questions asked by analysts during our sample period. Examples of these questions across different sustainability categories are presented in Appendix A.

Table 2 shows the distribution of sustainability-related questions classified into each of the 24 topics across the five sustainability dimensions.

[Insert Table 2 around here.]

¹⁴We thank Parabole.ai for sharing this pre-trained model and their discussions in deploying the model in the context of our study.

¹⁵The latest version of SASB standards include 26 disclosure topics. The two topics that are not included in our machine learning model are “Customer Welfare” and “Materials Sourcing”.

¹⁶The F1-score is calculated as $2 \times \frac{Precision \times Recall}{Precision + Recall}$ where $Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$ and $Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$

¹⁷Placing this into context, the F1-scores of the machine learning models used in Huang et al. (2022) for sentiment classification and ESG classification are 87.8% and 89.6%, respectively.

¹⁸We selected 1,328 analysts’ questions across the 24 different sustainability topics from our dataset using stratified random sampling. Based on our manual validation of these questions, we set the minimum threshold for the confidence score to 80% to balance between precision and recall model evaluation measures. Using this threshold the *out-of-sample* F1-score for our manually selected sample is 70%, while it reduces to 58% if we set the confidence score at 90%. For comparison, the out-of-sample F1-scores of different models presented in Booker et al. (2023) for sentiment classification of social media posts are between 56% and 84%. Nevertheless, an untabulated robustness test shows that our main inferences are unchanged upon raising the minimum threshold for confidence scores to 90%. We acknowledge that while it is virtually impossible to identify sustainability-focused analysts without error, it is difficult to explain why measurement error would drive our findings that sustainability-focused analysts (and in particular analysts who focus on material and financial impact-related sustainability issues) make forecasts that are both significantly more accurate and evoke stronger short-window market reactions than forecasts by non-sustainability-focused analysts covering the same firm.

The highest number of analyst questions relate to the *Competitive Behavior* topic, while the fewest questions relate to the *Human Rights and Community Relations* topic.¹⁹ In general, analysts’ questions are more directed to issues within the *Business Model & Innovation* and *Leadership & Governance* dimensions than the *Environmental, Social Capital* and *Human Capital* dimensions, although *Energy Management* and *Labor Practices* issues still receive substantial attention from analysts (corresponding to about 2% of all sustainability-related questions asked by analysts).

Finally, we create a proxy to identify analysts’ sustainability focus at the analyst-firm-year level.²⁰ *Sustainability Focused Analyst* is equal to one if, for a given firm-year, the analyst asks at least one sustainability-related question during any conference call in the 365-day period before issuing their forecast, and zero otherwise.²¹ In order to provide further insights into the potential mechanism through which sustainability focus may bolster analysts’ forecasting accuracy, we construct two additional indicator variables, namely *Material Sustainability Focused Analyst* and *Financial Impact Sustainability Focused Analyst*, which we discuss in detail in the following subsections.

3.2.2 Material Sustainability-Focused Analysts

The concept of materiality has long been a guiding principle for disclosure in the capital markets. As a general rule, firms must disclose material information to investors under

¹⁹In a later robustness test we show that our results are not solely driven by questions classified under the *Competitive Behavior* category.

²⁰The construction of our proxy at the analyst-firm-year level is consistent with the idea that the importance of ESG issues can change over time for a given firm (Serafeim and Yoon (2022b)). Indeed, when discussing firms’ investments in ESG, Edmans (2023, p. 20) points out that there are diminishing returns to such investments and that “the optimal level might vary over time and across firms”. A variety of time-varying forces can affect the dynamics of firms’ ESG activities. For example, Xu and Kim (2022) find that firms’ toxic emissions are higher when they are more financially constrained. Macroeconomic conditions can also play a role, as Edmans (2023, p.12) suggests that “one could argue that some ESG scandals are more likely in an up market – when times are good, companies get sloppy and don’t impose as tight controls.”

²¹Analysts in I/B/E/S who do not appear in conference call transcripts are included in our main sample and their number of sustainability-related questions are assigned a value of zero. However, we also estimate all of our models by excluding those analysts in I/B/E/S who do not ask any questions in the conference calls in the one-year period prior to their earning forecast. We find that sustainability-focused equity analysts continue to enjoy a competitive advantage when forecasting earnings compared to those analysts who participate in conference calls in the spirit of Mayew et al. (2013).

Generally Accepted Accounting Principles (GAAP), Securities and Exchange Commission (SEC) rules, and exchange reporting requirements (Heitzman et al., 2010). In many jurisdictions, materiality is the basis for determining whether a company may be exposed to fines or lawsuits for making a false or misleading statement about a material matter or for omitting information about a material matter (e.g., AASB, 2019; FASB, 2021). However, unlike financial disclosures that are only subject to materiality in the context of value creation for investors, sustainability disclosure frameworks are subject to materiality in the context of enterprise value creation, as well as materiality in the context of significant impacts on the economy, environment, and people. This is often called “double materiality” (Christensen et al., 2021).

SASB standards are designed to address the subset of sustainability topics that are most relevant for enterprise value creation (SASB, 2022). Specifically, SASB standards identify sustainability issues that are reasonably likely to have a significant effect on financial condition, operating performance, or market valuation within an industry. Hence, the inclusion of a sustainability issue in SASB standards for a specific industry requires evidence of both investor interest in the topic and the topic having a material impact on sustainability-related issues. Serafeim and Yoon (2022a) find that the market only reacts to financially material ESG news, and Khan et al. (2016) document that material sustainability ratings predict firm profitability. Hence, when examining analysts’ focus on sustainability issues, it is important to also capture their focus on sustainability issues that are material.

We rely on the Sustainable Industry Classification System[®] (SICS[®]) developed by the SASB to identify material sustainability issues for each specific firm. While major industry classification systems such as the Standard Industrial Classification (SICS), or the North American Industry Classification System (NAICS) use sources of revenue as their basis for classifying companies into specific sectors and industries, the SASB’s SICS[®] groups similar companies based on their sustainability-related risks and opportunities. This system

classifies companies into 77 industries across 11 sectors.^{22,23} At the highest level, the five main sustainability dimensions of *Environmental*, *Social Capital*, *Human Capital*, *Business Model & Innovation*, and *Leadership & Governance* serve as an organizing structure for the industry-specific topics covered in the SASB standards and are further defined by a subset of industry-agnostic General Issue Categories (G.I.C.s). As an example, in Figure 2 we present the structure of SASB’s classification structure for a material issue (*Greenhouse Gas (GHG) Emissions*) for firms in the *Oil and Gas – Exploration and Production* industry under the *Extractive and Minerals Processing* sector.

[Insert Figure 2 around here.]

For our proxy for material sustainability issues, we use the complete list of G.I.Cs that the SASB has identified for each company based on the industry in which the company is classified.²⁴ Specifically, *Material Sustainability Focused Analyst* is an indicator variable equal to 1 if the analyst asks at least one material sustainability-related question during a conference call in the 365-day period before issuing their forecast for a given firm-year, and zero otherwise.

3.2.3 Financial Impact Sustainability-Focused Analysts

We additionally investigate the extent to which analysts focus on the financial implications of sustainability issues by identifying sustainability-related questions posed by analysts that include terms relating to firm fundamentals. To operationalize this, we create a list of terms that relate to core firm fundamentals.²⁵ Next, we create an indicator variable *Fi-*

²²The complete list of SASB standards and SASB’s tool to determine SICS[®] for tens of thousands of companies around the globe can be found on SASB’s website: <https://www.sasb.org/standards/download/?lang=en-us> and <https://www.sasb.org/find-your-industry/>.

²³The SASB standards were developed and provisionally released one sector at time between 2012 to 2016, and then were officially approved in November 2018 by the SASB. For a detailed review of the SASB’s development process of these standards, see [Bochkay et al. \(2021\)](#).

²⁴We thank the IFRS Foundation for providing us with the SASB standards and the Sustainable Industry Classification System[®] (SICS[®]) for all companies in their database.

²⁵These terms include: “income”, “revenue”, “sale*”, “earning*”, “profit”, “expense*”, “loss*”, “bottom*line”, “gross margin”, “asset*”, “liability*”, or “equity*”

nancial Impact Sustainability Focused Analysts that takes a value of one when an analyst’s sustainability-related question includes at least one of these terms, and zero otherwise.

3.3 Analyst Forecast Accuracy

Prior studies show that an analyst’s forecast accuracy relative to her peers affects analyst turnover. By contrast, an analyst’s *absolute* forecast accuracy is not associated with turnover (Mikhail et al., 1999). Moreover, we are interested in whether focusing on sustainability imparts a competitive advantage to an analyst relative to her peers. Hence, following Clement and Tse (2005), we measure an analyst’s forecast accuracy relative to her peers as:

$$Relative\ Forecast\ Accuracy_{i,j,t} = \frac{Max\ Forecast\ Error_{i,t} - Forecast\ Error_{i,j,t}}{Max\ Forecast\ Error_{i,t} - Min\ Forecast\ Error_{i,t}}, \quad (1)$$

where i, j , and t represent firm, analyst, and year, respectively. $MaxForecastError_{it}$ and $MinForecastError_{it}$ are the maximum and minimum absolute forecast error among all analysts issuing a forecast for firm i in year t , respectively. The forecast error of analyst j for firm i in year t is calculated as the absolute difference between the analyst’s earning per share (EPS) forecast and the firm’s actual EPS:

$$Forecast\ Error_{i,j,t} = |Analyst\ EPS\ Forecast_{i,j,t} - Actual\ EPS_{i,t}| \quad (2)$$

The relative forecast accuracy measure lies between zero and one, where higher values indicate higher relative forecast accuracy. In a robustness test presented in Section 4.7, we show that our inferences are unchanged when we use alternative forecast accuracy measures similar to the one used in Hirshleifer et al. (2019) and Clement (1999).

4 Research Design and Results

4.1 Analyst Sustainability Focus and Forecast Accuracy

Our main test is based on estimating the following regression model:

$$\begin{aligned} \text{Relative Forecast Accuracy}_{i,j,t} = & \alpha + \beta_1 \text{Sustainability Focused Analyst}_{i,j,t} \\ & + \Sigma \beta_k \text{Analyst Characteristics}_{j,t} + \Sigma \beta_m \text{Firm Characteristics}_{i,t} \\ & + \Sigma \beta_n \text{Firm}_i + \Sigma \beta_n \text{Analyst}_j + \Sigma \beta_q \text{Year}_t + \varepsilon_{i,j,t}, \end{aligned} \tag{3}$$

where i , j , and t represent firm, analyst, and year, respectively. Consistent with prior research (e.g., Clement and Tse, 2005; Kumar, 2010; Jennings et al., 2017) we control for a set of time-variant analyst and firm characteristics associated with analyst forecast accuracy. Analyst characteristics include the forecast horizon (*Horizon*), the natural logarithm of brokerage size ($\text{Ln}(\text{Brokerage Size})$), the natural logarithm of analyst firm specific experience ($\text{Ln}(\text{Firm Specific Experience})$), the natural logarithm of analyst’s overall experience ($\text{Ln}(\text{Overall Experience})$), the natural logarithm of the number of firms that the analyst covers ($\text{Ln}(\text{Num Firms Following})$), and the natural logarithm of the number of industries the analyst covers ($\text{Ln}(\text{Num Industries Following})$). Firm characteristics include turnover of the firm’s shares during a given year (*Turnover*), annual stock return (*Return*), annual stock volatility (*Return Vol*), the natural logarithm of assets (*Size*), return on assets (*ROA*), the market-to-book ratio (*MTB*), the percentage of shares held by institutional investors (*Instown*), the natural logarithm of firm’s age ($\text{Ln}(\text{Firm Age})$), and the natural logarithm of the number of analysts covering the firm in a given year ($\text{Ln}(\text{Num Analyst Following})$). All variables are defined in detail in Appendix B. The analyst-firm-year nature of our research design allows us to exploit *within*-analyst and *within*-firm (*within*-analyst-firm) variation by including *analyst* and *firm* (*analyst-firm* fixed effects), that hold constant any time-invariant unobservable analyst and firm (analyst-firm) characteristics.²⁶

²⁶Following Brown (2001), in an untabulated robustness test, we also control for past relative forecast accuracy and our inferences are unchanged.

4.2 Descriptive Statistics

Table 3 presents summary statistics for the variables used in our analyses. The average forecast accuracy calculated based on the [Clement and Tse \(2005\)](#) measure is 78.9%. On average, analysts focus on sustainability for 19.9% of the firms that they cover in a given year (*Sustainability Focused Analyst*), of which 38.2% ($= \frac{0.076}{0.199}$) are focused on a material sustainability topic as defined by SASB, and 23.1% ($= \frac{0.046}{0.199}$) are focused on an financial impact-related sustainability issue. In our sample, 67.1% of the analysts participate in conference calls, in the sense that they ask at least one question in a conference call in the one-year period before they forecast earnings for a given firm.

[Insert Table 3 around here.]

Our descriptive statistics on analyst and firm characteristics used in this study are consistent with prior literature (e.g., [Jennings et al., 2017](#)). The average forecast horizon is 110 days, and there are an average of 60 analysts in a given brokerage house. The average time an analyst has followed a covered firm is around 4.5 years ($\approx 1,620$ days). The average time that the analyst has been covered in the I/B/E/S database, which we use as a proxy for analyst experience, is more than 12.7 years ($\approx 4,630$ days). Analysts follow 16 (4) firms (industries) on average. The average of the total number (length) of questions asked by an analyst during conference calls in the one year prior before they issue their forecast for a given firm is 6 (346). The median firm in our sample has a share turnover ratio of 1.08. Average annual stock return and stock volatility are both 12%. The average total assets of firms in our sample is \$2.5 billion. The average return on assets is -0.2% and the average institutional ownership is 71.3%. The average firm age is around 19 years and a firm is followed by 17 analysts in a given year on average.

4.3 Analyst Forecast Accuracy and Analyst Sustainability Focus

Panel A of Table 4 shows our results of estimating Eq. (3) using ordinary least squares (OLS). In columns (1) and (2), we include all analysts in our sample, whereas in columns (3) and (4), we estimate Eq. (3) on a sample that is restricted to *Participating Analysts*. In columns (1) and (3), we include analyst, firm, and year fixed effects individually in the regression model. We further demonstrate that the proxy we use to identify analysts' sustainability focus supports more robust inferences and facilitates more refined analyses which leverage its analyst-firm-level nature. To accomplish this, in columns (2) and (4) we include analyst-firm two-way fixed effects and year fixed effects.²⁷ The coefficient on *Sustainability Focused Analyst* across all models is positive and significant ($p < 0.01$), consistent with the idea that analysts' sustainability focus improves their forecast accuracy. In economic terms, the relative forecast accuracy of sustainability-focused analysts is 1.5% better than analysts who do not focus on sustainability. This improvement is equivalent to about 7% ($= \frac{0.0152}{0.218}$) of the standard deviation of relative forecast accuracy in our sample.²⁸ This effect is almost double the improvement in forecast accuracy documented by [Mayew et al. \(2013\)](#) and [Ke and Yu \(2006\)](#).²⁹

[Insert Table 4 around here.]

The coefficients on the control variables are consistent with prior research (e.g., [Ljungqvist et al., 2007](#); [Kumar, 2010](#); [Jennings et al., 2017](#); [Drake et al., 2020](#); [Fang and Hope, 2021](#); [Huang et al., 2022](#)). In particular, we find that forecast accuracy is lower for firms with higher

²⁷The number of observations in columns (2) and (4) is lower than those in columns (1) and (3), due to more singleton observations that are being dropped to robustly estimate these models ([Correia, 2015](#)).

²⁸Following [Mitton \(2021\)](#), we employ measures of economic significance that are scaled by the standard deviation of the dependent variable rather than the mean of the dependent variable. Following [Breuer and deHaan \(2024\)](#) we adjust the standard deviation of relative forecast accuracy for the fixed effects. Using the average relative forecast accuracy as the scaler, our estimate suggests that the improvement of the accuracy of sustainability-focused analysts is 2% of the average forecast accuracy in our sample.

²⁹For example, [Mayew et al. \(2013, p. 405\)](#) regress the change forecast accuracy on an indicator variable that identifies analysts that start participating in conference calls and report a coefficient of 1.205 on participating analysts which is 2.7% ($= \frac{1.205}{43.903}$) of the standard deviation of relative forecast accuracy in their sample.

return on assets, as well as for analysts from larger brokerage houses, and analysts with a longer forecast horizon.³⁰ Further, forecast accuracy is higher for larger firms and firms with higher institutional ownership.

In Panel B of Table 4, we re-estimate Eq. (3) by including the indicator variable that identifies *Material Sustainability Focused Analysts* in Eq. (3) to explore whether focusing on material sustainability issues enhances the competitive advantage enjoyed by sustainability-focused analysts. The coefficient on *Material Sustainability Focused Analysts* is positive and significant across all models ($p < 0.10$), indicating that there is an incremental increase in the forecast accuracy of analysts who focus on material sustainability issues compared to other sustainability-focused analysts. In economic terms, the relative forecast accuracy of material sustainability-focused analysts is 1.8% ($= 0.0043 + 0.0136$) better than analysts who do not focus on sustainability. This improvement is equivalent to 7.6% ($= \frac{0.0179}{0.235}$) of the standard deviation of relative forecast accuracy in our sample.

In Panel C of Table 4, we re-estimate Eq. (3) by including an indicator variable that identifies *Financial Impact Sustainability Focused Analysts* to explore whether focusing on the link between sustainability issues and financial impact enhances the forecasting advantage enjoyed by sustainability-focused analysts.³¹ The coefficient on *Financial Impact Sustainability Focused Analysts* is positive and significant across all models ($p < 0.10$), indicating that there is an incremental increase in forecast accuracy when analysts focus on the financial impact of sustainability issues relative to other sustainability-focused analysts. In economic terms, the relative forecast accuracy of sustainability-focused analysts who focus on sustainability issues in the context of their financial impact on the firm is 0.44% better than analysts who do not focus on sustainability. This improvement is equivalent to 2% ($= \frac{0.0044}{0.235}$) of the standard deviation of relative forecast accuracy in our sample.

³⁰Clement (1999) and Jacob et al. (1999) document a positive relation between forecast accuracy and brokerage size, whereas more recent studies (e.g., Drake et al., 2020; Fang and Hope, 2021; Huang et al., 2022) document a negative relation.

³¹Note that by definition this variable is the interaction term between *Financial Impact Analyst* and *Sustainability Focused Analysts*.

4.4 Sustainability Dimensions and Forecast Accuracy

As discussed in detail in Section 3.2.2, the SASB standards use five sustainability dimensions (i.e. Environment, Social Capital, Human Capital, Business Model & Innovation, and Leadership & Governance) as a high-level organizing structure for detailed categorization of sustainability issues. We use the issues classified in each sustainability dimension as per Table 2 to identify analysts' focus on each of the dimensions separately. Specifically, we define five separate indicator variables that are equal to one when an analyst asks about a sustainability issue that is classified under each of the five dimensions, and zero otherwise.

We next estimate Eq. (3) for each SASB-defined dimension of sustainability using these variables. The results are presented in Table 5.³² In Panel A, we examine whether forecast accuracy changes depending on the specific dimension of sustainability that an analyst focuses on. In Panel B, we examine the accuracy of analysts who focus on issues that are material to that specific dimension of sustainability. In Panel C, we examine the accuracy of analysts who focus on the financial impact of that specific dimension of sustainability.

In Panel A, the coefficient on *Sustainability Focused Analyst* is positive and significant ($p < 0.10$) for all dimensions. In Panel B, the coefficient on *Material Sustainability Focused Analyst* is positive and significant ($p < 0.05$) for all dimensions, except Human Capital. In Panel C, the coefficient on *Financial Impact Sustainability Focused Analyst* is positive and significant ($p < 0.05$) across all dimensions except for Environment, and Human Capital. Taken together, these results suggest that the positive association between analysts' sustainability focus and their forecast accuracy holds for the majority of SASB-defined sustainability subcategories.

[Insert Table 5 around here.]

³²The results tabulated from this section onward are estimated on all the analysts in our sample. However, our results are qualitatively similar if we limit our analyses to the *Participating Analysts* subset.

4.5 Stock Market Reaction

In this section, we examine the stock market's response to forecast revisions by sustainability-focused analysts. To do so, we estimate the following regression model:

$$\begin{aligned}
 \text{Three-Day } CAR_{i,j,t} = & \alpha + \beta_1 \text{ Forecast Revision}_{i,j,t} \times \text{Analyst}_{i,j,t} \\
 & + \beta_2 \text{ Forecast Revision}_{i,j,t} + \beta_3 \text{ Analyst}_{i,j,t} \\
 & + \Sigma \beta_k \text{ Analyst Characteristics}_{j,t} + \Sigma \beta_m \text{ Firm Characteristics}_{i,t} \\
 & + \Sigma \beta_n \text{ Firm}_i + \Sigma \beta_n \text{ Analyst}_j + \Sigma \beta_q \text{ Year}_t + \varepsilon_{i,j,t},
 \end{aligned} \tag{4}$$

where i , j , and t represent firm, analyst, and year, respectively. *Three-Day CAR* is the cumulative three-day abnormal return (adjusted for the Fama-French three-factor model) centered on the analyst's earnings forecast revision date. An analyst's forecast revision is calculated as:

$$\text{Forecast Revision}_{i,j,t} = \frac{\text{Analyst EPS Forecast}_{i,j,t_2} - \text{Analyst EPS Forecast}_{i,j,t_1}}{\text{Price}_{i,j,q}}, \tag{5}$$

where t_2 is the date of the latest one-year-ahead earnings forecast that is within 365 days to 30 days before the actual earnings announcement, and t_1 is the forecast immediately prior to that. $\text{Price}_{i,j,q}$ is the firm's share price on the earning announcement date. All other variables in Eq. (4) are similar to those included in Eq. (3).

The results of estimating Eq. (4) using OLS are presented in Table 6.³³ In columns (1) and (2), we replace *Analyst* in Eq. (4) with *Sustainability Focused Analyst*. In columns (3) and (4), we replace *Analyst* in Eq. (4) with *Material Sustainability Focused Analyst*. In columns (5) and (6), we replace *Analyst* in Eq. (4) with *Financial Impact Sustainability Focused Analyst*. In columns (1), (3), and (5), we include analyst, firm, and year fixed effects individually in the regression model. In columns (2), (4), and (6), we include analyst-firm two-way fixed effects and year fixed effects. The coefficient on *Forecast Revision* \times *Analyst* is positive and significant ($p < 0.10$) across all models, providing strong evidence

³³The number of observations for these analyses is lower than in our main analyses due to missing values for *Forecast Revision* and *Three-Day CAR* variables in our sample.

that the market returns are more sensitive to *Sustainability Focused Analyst*, *Material Sustainability Focused Analyst*, and *Financial Impact Sustainability Focused Analyst* forecast revisions relative to other analysts' forecast revisions. Specifically, the sensitivity of stock returns to revisions is almost 60% stronger for sustainability-focused analysts compared to non-sustainability-focused analysts. In fact, the sensitivity of returns to revisions almost doubles for material sustainability-focused analysts compared to non-sustainability-focused analysts, indicating that revisions by analysts who focus on material sustainability issues have particularly important valuation implications for investors.

[Insert Table 6 around here.]

4.6 Cross-Sectional Tests

In this section, we examine whether the relation between forecast accuracy and analysts' sustainability focus varies with analyst and firm characteristics by estimating the following regression model:

$$\begin{aligned}
 \text{Relative Forecast Accuracy}_{i,j,t} = & \alpha + \beta_1 \text{Sustainability Focused Analyst}_{i,j,t} \times \text{Cross-Sectional Variable}_{i,j,t} \\
 & + \beta_2 \text{Sustainability Focused Analyst}_{i,j,t} + \beta_3 \text{Cross-Sectional Variable}_{i,j,t} \\
 & + \Sigma \beta_k \text{Analyst Characteristics}_{j,t} + \Sigma \beta_m \text{Firm Characteristics}_{i,t} \\
 & + \Sigma \beta_n \text{Firm}_i + \Sigma \beta_n \text{Analyst}_j + \Sigma \beta_q \text{Year}_t + \varepsilon_{i,j,t},
 \end{aligned}
 \tag{6}$$

where we define *Cross-Sectional Variable* based on the following analyst and firm characteristics: analyst experience (*Experienced Analyst*) is an indicator equal to one when an analyst's overall experience is in the year-specific top tercile of our sample, and zero otherwise; firm size (*Small Firm*) is an indicator that is equal to one when firm size is in the year-specific bottom tercile of our sample, and zero otherwise; firm growth opportunities (*Growth Firm*) is an indicator that is equal to one when the firm's market-to-book-ratio is in the year-specific top tercile of our sample, and zero otherwise; and firm voluntary sustainability reporting (*Voluntary Sustainability Report*) which is an indicator that is equal to one when the firm

issued a voluntary sustainability report in the year before the analyst issues their forecast, and zero otherwise. The results of estimating Eq. (6) using OLS are presented in Table 7.

[Insert Table 7 around here.]

In column (1), the cross-sectional variable is *Experienced Analyst*. The coefficient on the interaction term is positive and significant ($p < 0.10$), indicating that more experienced analysts reap greater benefits from focusing on sustainability issues compared to less experienced analysts. This suggests that there is a learning curve associated with understanding how sustainability issues relate to firm performance. In column (2), the cross-sectional variable is *Small Firm*. The coefficient on the interaction term is positive and significant ($p < 0.05$), indicating that the increase in relative forecast accuracy associated with focusing on sustainability is incrementally higher when a sustainability-focused analyst is forecasting earnings for relatively smaller firms. In column (3), the cross-sectional variable is *Growth Firm*. The coefficient on the interaction term is positive and significant ($p < 0.01$), indicating that the increase in relative forecast accuracy is incrementally higher when a sustainability-focused analyst forecasts earnings for growth firms. Finally, in column (4), in the spirit of [Dhaliwal et al. \(2012\)](#), we examine whether the increase in relative forecast accuracy is driven by firms that issue a voluntary sustainability report (*Voluntary Sustainability Report*). The coefficient on the interaction term is negative, but not significant at conventional levels ($p > 0.10$). This result indicates that the increase in relative forecast accuracy of sustainability-focused analysts in our sample is not driven by firms' voluntary sustainability disclosures. In a broader sense, this confirms the contribution of our study above and beyond [Dhaliwal et al. \(2012\)](#) and [Muslu et al. \(2019\)](#) in that we provide new evidence suggesting that focusing on sustainability provides individual analysts a competitive edge in forecasting earnings over other analysts who cover the same company but do not focus on sustainability.

4.7 Robustness Tests and Additional Analyses

In this section we examine whether our main results are sensitive to different research design choices.

4.7.1 Voluntary Sustainability Reports

Using an international setting, [Dhaliwal et al. \(2012\)](#) and [Muslu et al. \(2019\)](#) find that analyst forecast errors are lower when firms issue voluntary ESG reports. However, recent empirical research does not document significant evidence of investors using voluntary sustainability reports for their investment decisions. For example, using Google searches as a proxy for stakeholder attention, [Ferguson et al. \(2022\)](#) show that the level of attention directed toward sustainability reports is very low compared to the level of attention directed toward financial and accounting information. In a similar vein, [Moss et al. \(2023\)](#) do not find evidence that retail investors react to ESG press releases. To examine whether the positive effect of analysts' sustainability focus on forecast accuracy is merely driven by firms' voluntary sustainability disclosure, we follow prior literature (e.g., [Lys et al., 2015](#)) and use proprietary data from corporateregister.com to identify whether firms issue voluntary sustainability reports. Corporateregister.com provides a global online directory of corporate sustainability reports going back to 1990.³⁴ Specifically, we include an indicator variable equal to 1 when a firm issues a voluntary sustainability disclosure (*Voluntary Sustainability Report*) in the year prior to the analyst's forecast, and zero otherwise, in Eq. (3). The results are presented in Panel A of Table 8. The coefficient on *Sustainability Focused Analyst* remains statistically significant ($p < 0.01$) and the magnitude is similar to our main analyses presented earlier in Table 4. The coefficient on *Voluntary Sustainability Report* is negative, but not significant at conventional levels ($p > 0.10$). This confirms that our inferences are not driven by firms' voluntary sustainability disclosures.

[Insert Table 8 around here.]

³⁴More information about this dataset can be found at https://www.corporateregister.com/about/CR_Data.pdf.

4.7.2 Analysts' General Information Acquisition During Conference Calls

A potential concern is that our results might be driven by the general information acquisition activity of analysts who participate in conference calls. To address this concern, we re-estimate Eq. (3) after controlling for the number of questions ($\ln(\text{Num Analyst Questions})$) and the length of all questions ($\ln(\text{Length Analyst Questions})$) that an analyst asks during conference calls in the one year prior to their earnings forecast. The results are presented in Panel B of Table 8. The coefficient on *Sustainability Focused Analyst* is positive and significant ($p < 0.01$) and the coefficient magnitude is comparable to those documented in Table 4, while the coefficients on both $\ln(\text{Num Analyst Questions})$ and $\ln(\text{Length Analyst Questions})$ are not statistically significant. This indicates that our inferences are not driven by analysts' general information acquisition during conference calls.

4.7.3 Excluding Analysts' Focus on Competitive Behavior

A potential concern is that our results might be driven by a single sustainability issue, rather than sustainability issues in general. Specifically, in our sample, 23.4% of analysts' sustainability-related questions comprise of questions about *Competitive Behavior*, which is under the *Leadership & Governance* sustainability dimension according to the SASB standards. To address this concern, we refine our main test variable *Sustainability Focused Analyst* to exclude sustainability questions that relate to *Competitive Behavior*. Next, we re-estimate Eq. (3) using this newly defined variable. The results are presented in Panel C of Table 8. The coefficient on *Sustainability Focused Analyst* is positive and significant ($p < 0.01$) and the coefficient magnitude is comparable to those documented in Table 4, indicating that our inferences are not driven by sustainability issues relating to Competitive Behavior.

4.7.4 Alternative Relative Forecast Accuracy Measures

While our main proxy for relative forecast accuracy following Clement and Tse (2005) adjusts analysts' forecast accuracy based on their peer group (i.e., all analysts that issue forecasts for the same firm in a given year), a potential concern is that this measure is not

adjusted for the different horizons of analysts' forecasts. To mitigate this concern, we follow [Hirshleifer et al. \(2019\)](#) and calculate relative forecast accuracy as:

$$\text{Relative Forecast Accuracy HLLT}_{i,j,t} = \frac{\text{Median Forecast Error}_{i,t-t-90\text{days}} - \text{Forecast Error}_{i,j,t}}{\text{Std Forecast Error}_{i,t-t-90\text{days}}}, \quad (7)$$

where i , j , and t represent firm, analyst, and year. *Forecast Error* is similar to the one calculated in Eq. (2). *Median Forecast Error* is calculated as the median of forecast errors among analysts issuing a forecast in the 90-day period before analyst j 's earnings forecast for firm i . By using the 90-day window, we ensure that relative forecast accuracy is calculated among analysts with a comparable forecast horizon.

We re-estimate Eq. (3) using *Relative Forecast Accuracy HLLT* as the dependent variable. The results are presented in Panel D of Table 8. The coefficient on *Sustainability Focused Analyst* remains positive and statistically significant ($p < 0.01$), in line with our main results.

Moreover, in Panel E of Table 8, we follow the approach in [Clement \(1999\)](#) and use -1 times mean adjusted absolute forecast error for each analyst as the dependent variable and demean all the analyst-level control variables and estimate Eq. (3) without including firm-level control variables and the fixed effects. The coefficient on *Sustainability Focused Analyst* remains positive and statistically significant ($p < 0.01$), in line with our main results.

4.7.5 Alternative Analyst Sustainability Focus Measure

In a robustness test, we re-estimate Eq. (3) using the number of sustainability-related questions that the analyst asks during conference calls in the year before they issue their forecast (*Num Sustainability Focused Questions*) instead of the *Sustainability Focused Analyst* indicator variable. The results are presented in Panel F of Table 8. The coefficient on *Num Sustainability Focused Questions* is positive and statistically significant ($p < 0.01$), indicating that greater sustainability focus is associated with greater improvements in forecast accuracy.

4.7.6 Alternative Forecast Horizons

Our main focus in the preceding tests is on one-year-ahead earnings forecasts. If the effect of sustainability issues on firm performance mostly manifests over longer horizons as suggested by prior literature (e.g. [Edmans, 2021, 2022](#); [Khan et al., 2016](#); [Aghamolla and An, 2021](#)) we expect that the accuracy of two-year-ahead forecasts will be also affected by analysts' sustainability focus. To investigate this we replicate our analyses for two-year-ahead forecasts. The results are presented in Panel G of Table 8. The coefficient on *Sustainability Focused Analyst* is positive and statistically significant ($p < 0.05$). These results are consistent with sustainability being an important driver of firms' long-term performance.

4.7.7 ESG Incidents

A potential concern is that firms' ESG incidents solely drive analysts' sustainability questions, and therefore, ESG incidents subsume the effect of analyst sustainability focus when predicting analysts' forecast accuracy. To address this, we follow the approach in [Derrien et al. \(2022\)](#) and control for the occurrence of an ESG incident during the fiscal year. The result of this analysis is presented in Panel H of Table 8. We continue to find that analysts' sustainability focus is positively related to their forecast accuracy after controlling for *ESG Incidents*.

Taken together, the results presented in Table 8 indicate that our main inferences on the positive association between analysts' sustainability focus and forecast accuracy are not sensitive to different design choices.

4.8 Determinants of Analysts' Sustainability Focus

Our primary analyses study the forecasting implications of analysts' focus on sustainability issues. However, because this study is the first to document analysts' focus on sus-

tainability issues, we believe it is important to understand what leads analysts to focus on sustainability. To do this, we estimate regression models taking the form:

$$\begin{aligned} \text{Sustainability Focused Analyst}_{i,j,t} = & \alpha + \Sigma\beta_k \text{Analyst Characteristics}_{j,t} \\ & + \Sigma\beta_m \text{Firm Characteristics}_{i,t} + \Sigma\beta_n \text{Firm}_i + \Sigma\beta_n \text{Analyst}_j + \Sigma\beta_q \text{Year}_t + \varepsilon_{i,j,t}, \end{aligned} \quad (8)$$

where i , j , and t represent firm, analyst, and year. We include analyst and firm characteristics from our main analyses that are potentially associated with analysts' sustainability focus. The analyst characteristics include $\text{Ln}(\text{Brokerage Size})$, $\text{Ln}(\text{Firm Specific Experience})$, $\text{Ln}(\text{Overall Experience})$, $\text{Ln}(\text{Num Firms Following})$, and $\text{Ln}(\text{Num Industries Following})$. The firm characteristics include Turnover , Return , Return Vol , Size , ROA , MTB , Instown , $\text{Ln}(\text{Num Analyst Following})$, and $\text{Voluntary Sustainability Report}$. To further shed light on the determinants of sustainability focus, in additional analysis we replace the dependent variable with *Material Sustainability Focused Analyst* and *Financial Impact Sustainability Focused Analyst*. We note that all the models include analyst or analyst-firm fixed effects to control for unobservable time-invariant analyst or analyst-firm combination characteristics.

The results of estimating Eq. (8) using OLS are presented in Table 9.³⁵ In columns (1)–(3) we examine factors that are associated with analysts' sustainability focus in general (*Sustainability Focused Analyst*). In columns (4)–(6) we examine factors that are associated with analysts' material sustainability focus (*Material Sustainability Focused Analyst*). In columns (7)–(9) we examine factors that are associated with analysts' sustainability focus in the context of its impact on firm fundamentals (*Financial Impact Sustainability Focused Analyst*). Analyst sustainability focus is positively associated with analyst experience, which dovetails with our earlier finding that there is a learning curve associated with focusing on

³⁵Our results are robust to using logistic regression. We tabulate the results of OLS regressions instead of nonlinear methods (e.g. logit or probit) because it is impossible to use maximum likelihood estimation methods for analyst-firms observations that never take on a value of 1 for *Sustainability Focused Analyst* due to the "complete or quasi-complete separation problem". Moreover, for dichotomous dependent variables, OLS coefficient estimates remain unbiased, especially in large samples (Wooldridge, 2010).

sustainability in that more experienced analysts reap greater benefits when they focus on sustainability compared to less experienced analysts.³⁶

Regarding the types of firm characteristics that lead analysts to focus on sustainability, we find that analysts are more likely to focus on sustainability for small firms and those with low analyst following. This is consistent with analysts focusing on sustainability when information asymmetry is greater and comports with our earlier finding that analysts reap greater benefits in terms of forecast accuracy when they focus on sustainability for small firms and growth firms. Further, we document some evidence that the issuance of a voluntary sustainability report is positively associated with sustainability focus, and stock returns are negatively associated with sustainability focus.

[Insert Table 9 around here.]

5 Conclusion

There is significant debate regarding the incorporation of sustainability into the investment process (e.g. [Starks, 2023](#); [Giglio et al., 2023](#); [Ackerman and Wise, 2023](#)). We propose a novel method for measuring equity analysts' focus on sustainability issues by analyzing their questions during conference calls. We exploit recent advances in natural language processing and use a machine learning BERT-based model to classify questions using the SASB's sustainability dimensions. This approach offers future researchers a methodology to detect sustainability-related content in other types of text, such as corporate disclosures and social media. Using the classifications from this model, we examine whether sustainability-focused analysts enjoy a competitive advantage in forecasting earnings.

Our main result is that when an analyst focuses on sustainability for a covered firm, her earnings forecast accuracy improves relative to other analysts who cover the same firm.

³⁶We also find that analysts who cover more stocks are more likely to focus on sustainability, consistent with the view that exposure to a broad set of firms leads analysts to recognize and focus on shared performance drivers such as sustainability.

Moreover, analysts who focus on material sustainability issues make even more accurate forecasts. We also find that the stock market reacts significantly more strongly when an analyst focuses on sustainability. Taken together, our findings are consistent with the view that considering sustainability issues provides a competitive edge when forecasting earnings. These results have practical implications for investment professionals and policymakers, who are increasingly interested in the role of sustainability in investing and enterprise value creation.

Appendix A: Examples of Analysts' Sustainability Questions by Topic

Sustainability Dimension	Sustainability Topic	Analyst Question	Firm Name and Ticker	Date of the Call
Environment	Energy Management	Okay. On the energy commentary I guess intuitively I would think there might be a little bit more pressure given some of the heating cost in winter and that might have a bigger impact, but it seems... your comment seem to indicate that you might be able to deal with these costs better, so if you could maybe provide some more color there?	Service Corporation International (NYSE:SCI)	7-Aug-08
	GHG Emissions	I think you've all done a great job in terms of the cost reduction efforts and being able to increase margins in the face of some very difficult industry fundamentals. First question, I wanted to ask about – in your ESG presentation, you had a Permian model case study in there about greenhouse gas emissions at the wellhead. And there seems to be more attention from the majors and large independents in terms of trying to reduce the greenhouse gas emissions at the wellhead. Can you maybe talk a little bit more about your role there and what that market opportunity is?	Team, Inc. (NYSE:TISI)	5-Nov-20
	Water & Wastewater Management	My water vocabulary is also challenged. So just wanted to ask for some clarification. My understanding at least is that there's a few pathways in the water business. One is the disposal, cleaning it up through Clearwater and putting it into, I guess, nearby water bodies, et cetera. The other is recycling and there might be other aspects of it. But could you kind of clarify where these savings are occurring, first of all? And second of all, what remaining aspects of the water handling are future challenges? And then finally, is the water stuff discussed on the print today, is it 100% application? Or are you easing into it in 2020?	Antero Resources Corporation (NYSE:AR)	1-Aug-19
Social Capital	Data Security	Could you talk about how much you're needing to spend or investing in platform security just given overall data privacy concerns and the concerns over the abuse – or misuse of the platforms by third-party – by bad actors out there, how much has that caused you to increase spend on platform security this year or for the next couple of years?	Twitter, Inc. (NYSE:TWTR)	25-Apr-18
	Employee Health & Safety	That's good to hear. And just you probably wouldn't expect this comment, but since you brought it up in the prepared remarks and your comment here about checking on employees during the fires, the safety record, because it – our understanding is some of the most dangerous professions are forestry, mining and landscaping, and for you to turn around and say that you've got 20% improvement and some of the branches have 0 instances of accidents. So what are you doing special there?	BrightView Holdings, Inc. (NYSE:BV)	28-Nov-18
	Product Quality & Safety	It's Steve Anderson from Maxim Group. You mentioned today about a more of a focus on food safety, sustainability, better sourcing. I want to ask if you've – there's been any new incremental spending that you're looking to do to ensure a higher degree of food safety?	Buffalo Wild Wings, Inc. (Nasdaq:BWLD)	16-Aug-16

	Selling Practices and Product Labeling	Just 2 questions. One, as a result of the settlement with Nestlé, do have any restrictions in terms of like claims you can make? Or do you have to make any changes to your labels, and again, ingredients or things?	Blue Buffalo Pet Products, Inc. (Nasdaq:BUFF)	10-Nov-16
Business Model & Innovation	Business Model Resilience	Good afternoon, Roger. You had incredible resilience in the parts and service business over the last couple of quarters. And a 7% increase in the fourth-quarter in the US was a pretty big increase, better than what we're expecting. I was just wondering if you could give us some color as to why that has been so resilient and has remained so profitable at a period of time, where it seems like there should be a tail and some weakness in that business?	Penske Automotive Group, Inc. (NYSE:PAG)	16-Feb-11
	Physical Impacts of Climate Change	Sandy, I'm not sure if you talked on the expense side. I dropped off for a minute. But was there any expense impact with Hurricane Sandy that will impact the expenses in December quarter beyond what's normally expected?	Globecomm Systems Inc. (Nasdaq:GCOM)	7-Nov-12
	Product Design & Lifecycle Management	Okay, great. On the ultrasound product, and I'm certainly no expert on the medical side of this, based on the current generation of products, how long do you expect the cycle to last? At what point do you expect to have to introduce upgraded products?	Analogic Corporation (Nasdaq:ALOG)	20-Sep-11
	Supply Chain Management	Okay, got it. That's great color. I also wanted to turn more broadly to the supply chain. You had mentioned some pretty big backlog increases, of course. You also mentioned in your press release, there's been some stretching of some of your lead times. Are you finding any components, or perhaps, current parts and assemblies in short supply right now? Or are the sort of the lead times simply bottlenecks at your own facilities, where you just have so much demand you can't catch up?	Alamo Group Inc. (NYSE:ALG)	2-Mar-18
Leadership & Governance	Competitive Behavior	Looking at the results in China, you definitely have some strength versus competitors. How much of that is due to the Bonvoy marketing versus the partnership with Alibaba, the Fliggy?	Marriott International, Inc. (NasdaqGS:MAR)	6-Aug-19
	Management of the Legal & Regulatory Environment	Awesome. All right. And George, could you remind me or, I guess, possibly update me your current expectations in terms of regulatory approvals in the 3 Asian countries for XenoSure? And also, if you have the current enrollment in China for XenoSure, that would be awesome.	LeMaitre Vascular, Inc. (NasdaqGM:LMAT)	1-May-19

Appendix B: Variable Descriptions

Variable Name	Description
<i>Brokerage Size</i>	Number of analysts in a specific brokerage firm
<i>ESG Incidents</i>	Equal to 1 if the firm had any ESG incidents reported in the RepRisk database during the fiscal year, zero otherwise
<i>Experienced Analyst</i>	Equal to 1 if analyst's experience is in the year-specific top tercile of our sample, and zero otherwise.
<i>Financial Impact Sustainability Focused Analyst</i>	Equal to 1 if the analyst asks a Sustainability question that includes any of the words "asset*", "bottom line", "bottom-line", "bottomline", "earning*", "equity", "expense*", "gross margin", "income", "liability", "liabilities", "loss", "losses", "profit*", "revenue*", or "sale*" in a conference call hosted by the covered firm in the one year before they issue their forecast, zero otherwise
<i>Firm Age</i>	The difference between the end of fiscal year and the first day that the firm appeared on Compustat
<i>Firm Specific Experience</i>	Number of days between the first date the analyst started covering the firm until the day of the forecast
<i>Forecast Accuracy Clement</i>	-1 times the difference between analyst forecast error and the average forecast errors of all analysts for a given firm-year, scaled by the average forecast errors of all analysts for a given firm-year
<i>Growth Firm</i>	Equal to 1 if firm market-to-book ratio is in the year-specific top tercile of our sample, and zero otherwise.
<i>Horizon</i>	The number of days between analyst forecast and earnings announcement date
<i>Instown</i>	The proportion of shares owned by institutional investors
<i>Length Analyst Questions</i>	Number of words in all questions asked by the analyst during conference calls hosted by the covered firm in the one year they issue their forecast
<i>Material Sustainability Focused Analysts</i>	Equal to 1 if the analysts ask a question regarding a material Sustainability topic in a conference call hosted by the covered firm in the one year before they issue their forecast, zero otherwise
<i>MTB</i>	Market value of equity divided by book value of equity
<i>Num Analyst Following</i>	Number of analysts following the firm
<i>Num Analyst Questions</i>	Number of all questions asked by the analyst during conference calls hosted by the covered firm in the one year they issue their forecast
<i>Num Sustainability Focused Questions</i>	Total number of Sustainability questions asked by an analyst in a conference call hosted by the covered firm in the one year before they issue their forecast
<i>Num Firms Covered</i>	Number of firms that the analyst covers in a given year
<i>Num Industries Covered</i>	Number of unique two-digit SIC codes of firms that the analyst covers in a given year
<i>Overall Experience</i>	The number of days between the first date that the analyst appeared in IBES database and the day of the forecast
<i>Participating Analyst</i>	Equal to 1 if the analyst asks at least one question in a conference call hosted by the covered firm in the one year before they issue their forecast, zero otherwise
<i>Relative Forecast Accuracy</i>	The maximum analysts forecast error among all analysts forecasting for the same firm in a given year minus focal analyst's forecast error scaled by the difference between maximum and minimum among all analysts forecast error forecasting for the same firm in a given year.
<i>Relative Forecast Accuracy HLLT</i>	The difference between median of analyst forecast errors within the same 90 days and the focal analyst forecast error scaled by standard deviation of all forecast errors within the same 90 dates
<i>Return</i>	Cumulative stock return of the firm over the past 12 months
<i>Return Vol</i>	Standard deviation of firm monthly returns over the past 12 months
<i>Revision</i>	The difference between analysts' current forecast and their immediate last forecast scaled by price on earning announcement date
<i>ROA</i>	Income before extraordinary items scaled by total assets
<i>Size</i>	Natural logarithm of 1 plus total assets
<i>Small Firm</i>	Equal to 1 if firm size is in the year-specific bottom tercile of our sample, and zero otherwise.
<i>Sustainability Focused Analyst</i>	Equal to 1 if the analyst asks a Sustainability question in a conference call hosted by the covered firm in the one year before they issue their forecast, zero otherwise
<i>Three-Day CAR</i>	3-day abnormal return adjusted for Fama-French 3 factors model around analyst forecast revision date
<i>Turnover</i>	Natural logarithm of 1 plus the ratio of total share volume scaled by the number of shares outstanding
<i>Voluntary Sustainability Report</i>	Equal to 1 if the firm issued a voluntary Sustainability report in the year before analysts forecast, zero otherwise

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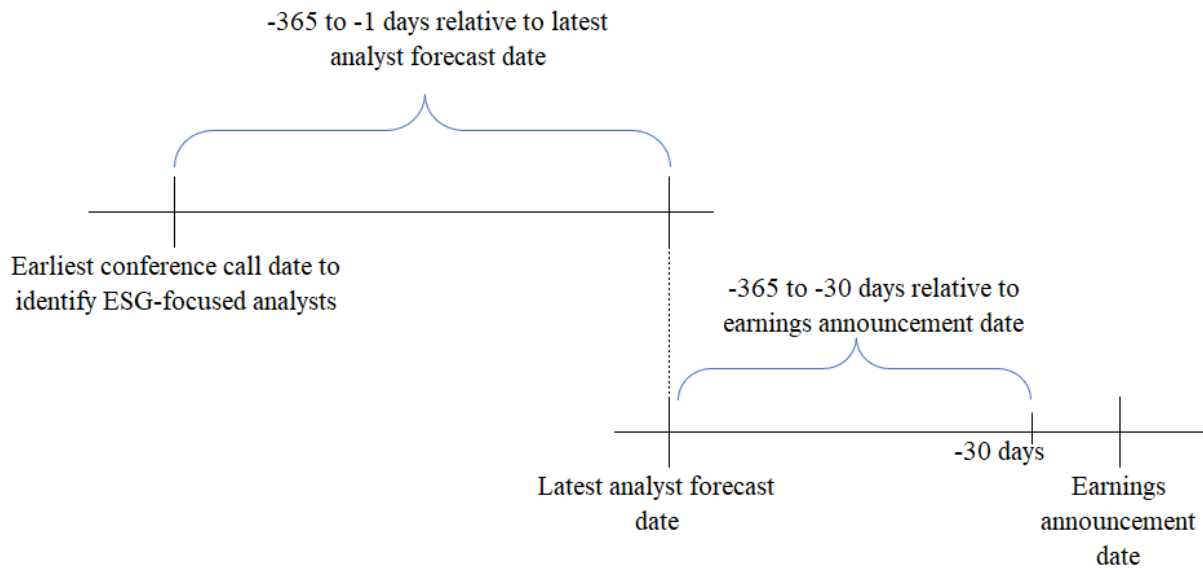


Figure 1. Timeline for Identifying Sustainability-Focused Analysts
 This figure shows the timeline for identifying Sustainability-focused analysts in our research design.

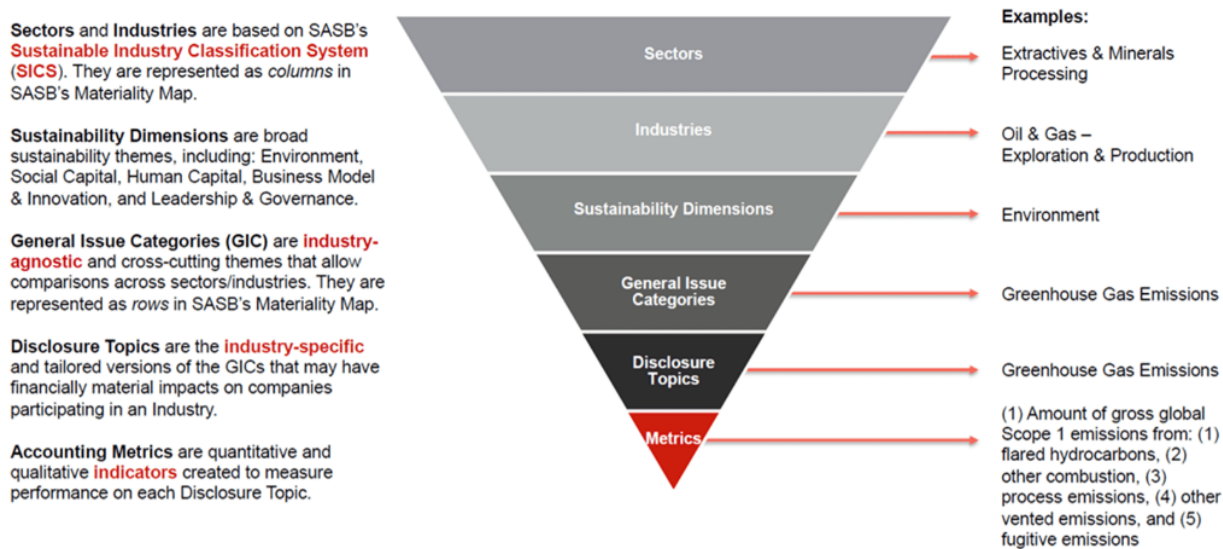


Figure 2. An Example of the Structure of the SASB Standards

This figure shows an example of a material Sustainability issue (GHG Emissions) for the Extractive and Minerals Processing industry. Source: https://www.sasb.org/wp-content/uploads/2021/07/PCP-package_vF.pdf.

Table 1. Sample Selection

Procedure	Number of Observations
I/B/E/S Detail analysts last forecast for the next fiscal year (FPE=1) with non-missing values for analyst forecast accuracy and analyst characteristic variables during fiscal years 2008-2020 after excluding forecasts that are more than one year or less than one month away from the earnings announcement day	551,054
Matching with CRSP and Compustat with non-missing values on firm characteristics	301,732
Eliminating observations with missing CapitalIQ Company ID and unmatched analysts with CapitalIQ	272,096
Number of corresponding conference calls	111,789
Number of corresponding transcript questions from CapitalIQ	1,849,827
Eliminating corresponding transcript questions from CapitalIQ with less than 10 words	1,581,482
Number of Sustainability question transcripts	102,113
Number of Sustainability analysts-firm-years	54,168 (20% of all the observations in our sample)
Number of conference calls with at least one Sustainability question	52,820 (47% of all conference calls in our sample)
Average ratio of Sustainability-focused analysts to all analysts who cover a firm in a given year	33%

This table presents the sample selection process for the analyses in this paper. The final sample constitutes 272,096 analyst-firm-year observations during 2008–2020.

Table 2. Frequency of Sustainability Issues among Questions of Sustainability Focused Analysts

Sustainability Dimension	Sustainability Issue	Frequency	Frequency Percentage
<i>Environment</i>	GHG Emissions	162	0.16
	Air Quality	88	0.09
	Energy Management	1,959	1.92
	Waste and Hazardous Materials Management	267	0.26
	Water and Wastewater Management	412	0.4
	Ecological Impacts	146	0.14
<i>Social Capital</i>	Human Rights and Community Relations	7	0.01
	Customer Privacy	110	0.11
	Data Security	781	0.76
	Access and Affordability	121	0.12
	Product Quality and Safety	395	0.39
	Selling Practices and Product Labeling	74	0.07
<i>Human Capital</i>	Labor Practices	2,070	2.03
	Employee Health and Safety	309	0.3
	Employee Engagement Inclusion and Diversity	585	0.57
<i>Business Model & Innovation</i>	Product Design and Lifecycle Management	17,200	16.84
	Business Model Resilience	1,497	1.47
	Supply Chain Management	4,316	4.23
	Physical Impacts of Climate Change	509	0.5
<i>Leadership & Governance</i>	Critical Incident Risk Management	191	0.19
	Management of Legal and Regulatory Framework	23,931	23.44
	Competitive Behavior	32,489	31.82
	Business Ethics	291	0.28
	Systemic Risk Management	14,203	13.91

This table presents the frequencies of analysts' questions in our sample categorized across 24 Sustainability issues within five Sustainability dimensions.

Table 3. Descriptive Statistics

	N	Mean	SD	Q1	Median	Q3
Dependent Variables:						
<i>Relative Forecast Accuracy</i>	272096	0.789	0.235	0.705	0.875	0.957
<i>Relative Forecast Accuracy HLLT</i>	263615	-0.013	0.918	-0.421	0	0.535
<i>Forecast Accuracy Clement</i>	272096	0.353	0.593	0.094	0.51	0.782
<i>Three-Day CAR</i>	218355	0	0.066	-0.026	0	0.026
Test Variables:						
<i>ESG Focused Analyst</i>	272096	0.199	0.399	0	0	0
<i>Financial Impact ESG Focused Analyst</i>	272096	0.046	0.210	0	0	0
<i>Material ESG Focused Analyst</i>	272096	0.076	0.265	0	0	0
<i>Participating Analyst</i>	272096	0.671	0.47	0	1	1
<i>Revision</i>	218355	-0.004	0.052	-0.003	0	0.002
Analyst Characteristics:						
<i>Horizon</i>	272096	110.514	70.502	62	97	120
<i>Brokerage Size</i>	272096	60.999	54.087	18	42	93
<i>Firm Specific Experience</i>	272096	1620.522	1678.639	403	1049	2292
<i>Overall Experience</i>	272096	4630.86	3253.849	1946	3892	6992
<i>Num Firms Covered</i>	272096	16.407	7.15	12	16	20
<i>Num Industries Covered</i>	272096	4.276	2.405	2	4	6
<i>Num Analyst Questions</i>	272096	6.118	7.554	0	4	9
<i>Length Analyst Questions</i>	272096	346.211	435.129	0	212	522
Firm Characteristics:						
<i>Turnover</i>	272096	1.145	0.485	0.799	1.076	1.42
<i>Return</i>	272096	0.117	0.468	-0.17	0.073	0.324
<i>Return Vol</i>	272096	0.118	0.067	0.071	0.101	0.145
<i>Size</i>	272096	7.816	1.847	6.544	7.817	9.04
<i>ROA</i>	272096	-0.002	0.059	-0.006	0.011	0.024
<i>MTB</i>	272096	4.062	7.57	1.515	2.667	4.81
<i>Instown</i>	272096	0.713	0.302	0.628	0.823	0.929
<i>Firm Age</i>	272096	6978.848	3805.846	3562	6940	10227
<i>Num Analyst Following</i>	272096	17.271	10.347	9	15	24
<i>ESG Incidents</i>	272096	0.357	0.479	0	0	1

This table presents reports descriptive statistics of variables used in our analyses throughout the paper. All variables are defined in Appendix B. All variables are winsorized at the 1st and 99th percentiles.

Table 4. Sustainability-Focused Analysts and Relative Forecast Accuracy

Panel A: Sustainability Focused Analysts				
Dependent Variable= Analysts Sample=	<i>Relative Forecast Accuracy</i>			
	All		Participating	
	(1)	(2)	(3)	(4)
<i>Sustainability Focused Analyst</i>	0.0152*** (12.4203)	0.0157*** (11.2239)	0.0147*** (11.4458)	0.0159*** (10.9032)
<i>Horizon</i>	-0.0011*** (-113.9459)	-0.0011*** (-104.3764)	-0.0011*** (-97.1496)	-0.0011*** (-88.6222)
<i>Ln(Brokerage Size)</i>	-0.0060*** (-4.6437)	-0.0037** (-2.4956)	-0.0068*** (-4.4539)	-0.0039** (-2.2512)
<i>Ln(Firm Specific Experience)</i>	0.0011*** (2.7858)	0.0013** (2.0261)	-0.0010 (-1.5637)	-0.0018 (-1.3863)
<i>Ln(Overall Experience)</i>	-0.0021 (-1.3553)	-0.0031 (-1.6025)	-0.0017 (-0.7918)	-0.0023 (-0.8043)
<i>Ln(Num Firms Covered)</i>	0.0022 (1.0182)	0.0038 (1.6081)	0.0028 (1.0584)	0.0024 (0.7805)
<i>Ln(Num Industries Covered)</i>	0.0014 (0.7524)	0.0025 (1.1683)	0.0015 (0.6498)	0.0044* (1.6867)
<i>Turnover</i>	0.0041** (2.5182)	0.0035* (1.9481)	0.0036* (1.7865)	0.0033 (1.5002)
<i>Return</i>	-0.0027** (-2.4129)	-0.0013 (-1.0547)	-0.0024* (-1.8721)	-0.0006 (-0.4079)
<i>Return Vol</i>	0.1073*** (9.1673)	0.1070*** (8.3951)	0.1104*** (7.7548)	0.1101*** (7.0702)
<i>Size</i>	0.0005 (0.3527)	-0.0018 (-0.9497)	0.0023 (1.2366)	-0.0003 (-0.1339)
<i>ROA</i>	-0.0425*** (-3.1505)	-0.0580*** (-3.9130)	-0.0498*** (-2.9869)	-0.0716*** (-3.8896)
<i>MTB</i>	0.0000 (0.4834)	0.0000 (0.1300)	0.0001 (1.2293)	0.0001 (1.2904)
<i>Instown</i>	0.0087*** (2.8619)	0.0087** (2.5064)	0.0069* (1.8356)	0.0115*** (2.7134)
<i>Ln(Firm Age)</i>	0.0181*** (4.8353)	0.0124** (2.5716)	0.0091** (1.9720)	0.0020 (0.3440)
<i>Ln(Num Analyst Following)</i>	0.0423*** (17.8339)	0.0446*** (15.6858)	0.0362*** (13.0125)	0.0371*** (11.1001)
Observations	272,096	254,360	182,144	168,318
Adjusted R-squared	0.2087	0.2230	0.2061	0.2177
Analyst FEs	Yes	No	Yes	No
Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	No	Yes	No
Analyst-Firm FEs	No	Yes	No	Yes
Cluster	Analyst	Analyst	Analyst	Analyst

Table 4. (Continued)

Panel B: SASB Material Sustainability Focused Analysts				
Dependent Variable= Analysts Sample=	<i>Relative Forecast Accuracy</i>			
	All		Participating	
	(1)	(2)	(3)	(4)
<i>Material Sustainability Focused Analyst</i>	0.0043** (2.0505)	0.0067*** (2.9377)	0.0040* (1.8971)	0.0062*** (2.5834)
<i>Sustainability Focused Analyst</i>	0.0136*** (9.2109)	0.0132*** (7.9381)	0.0134*** (8.5189)	0.0138*** (7.7203)
<i>Horizon</i>	-0.0011*** (-113.9518)	-0.0011*** (-104.3710)	-0.0011*** (-96.8887)	-0.0011*** (-87.9630)
<i>Ln(Brokerage Size)</i>	-0.0060*** (-4.6478)	-0.0037** (-2.4976)	-0.0067*** (-4.3140)	-0.0037** (-2.0861)
<i>Ln(Firm Specific Experience)</i>	0.0010*** (2.7748)	0.0013** (2.0202)	-0.0012* (-1.8725)	-0.0022* (-1.7264)
<i>Ln(Overall Experience)</i>	-0.0021 (-1.3520)	-0.0031 (-1.5995)	-0.0017 (-0.7705)	-0.0023 (-0.8038)
<i>Ln(Num Firms Covered)</i>	0.0022 (1.0231)	0.0038 (1.6209)	0.0022 (0.8175)	0.0015 (0.4902)
<i>Ln(Num Industries Covered)</i>	0.0014 (0.7532)	0.0025 (1.1696)	0.0025 (1.0805)	0.0060** (2.2665)
<i>Turnover</i>	0.0041** (2.5280)	0.0035** (1.9684)	0.0036* (1.7975)	0.0034 (1.5100)
<i>Return</i>	-0.0027** (-2.4213)	-0.0013 (-1.0654)	-0.0032** (-2.4563)	-0.0013 (-0.9335)
<i>Return Vol</i>	0.1074*** (9.1741)	0.1071*** (8.4043)	0.1030*** (6.9269)	0.1043*** (6.4474)
<i>Size</i>	0.0005 (0.3503)	-0.0018 (-0.9491)	0.0019 (1.0219)	-0.0003 (-0.1476)
<i>ROA</i>	-0.0425*** (-3.1500)	-0.0580*** (-3.9150)	-0.0504*** (-2.9130)	-0.0687*** (-3.6077)
<i>MTB</i>	0.0000 (0.4876)	0.0000 (0.1345)	0.0002* (1.8653)	0.0002** (2.0710)
<i>Instown</i>	0.0087*** (2.8501)	0.0086** (2.4869)	0.0142*** (3.4169)	0.0182*** (3.8701)
<i>Ln(Firm Age)</i>	0.0181*** (4.8417)	0.0124** (2.5742)	0.0073 (1.5468)	0.0011 (0.1743)
<i>Ln(Num Analyst Following)</i>	0.0423*** (17.8399)	0.0446*** (15.6902)	0.0359*** (12.6716)	0.0364*** (10.7317)
Observations	272,096	254,360	175,588	162,416
Adjusted R-squared	0.2088	0.2231	0.2067	0.2192
Analyst FEs	Yes	No	Yes	No
Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	No	Yes	No
Analyst-Firm FEs	No	Yes	No	Yes
Cluster	Analyst	Analyst	Analyst	Analyst

Table 4. (Continued)

Dependent Variable= Analysts Sample=	<i>Relative Forecast Accuracy</i>			
	All		Participating	
	(1)	(2)	(3)	(4)
<i>Financial Impact Sustainability Focused Analyst</i>	0.0039* (1.7512)	0.0044* (1.7256)	0.0043* (1.9189)	0.0044* (1.7256)
<i>Sustainability Focused Analyst</i>	0.0137*** (10.3189)	0.0143*** (9.4497)	0.0135*** (9.8524)	0.0143*** (9.4497)
<i>Financial Impact Analyst</i>	0.0028*** (2.6524)	0.0026** (2.0905)	0.0025** (2.1390)	0.0026** (2.0905)
<i>Horizon</i>	-0.0011*** (-113.9203)	-0.0011*** (-104.3671)	-0.0011*** (-97.1228)	-0.0011*** (-104.3671)
<i>Ln(Brokerage Size)</i>	-0.0061*** (-4.6971)	-0.0038** (-2.5408)	-0.0069*** (-4.4815)	-0.0038** (-2.5408)
<i>Ln(Firm Specific Experience)</i>	0.0009** (2.2890)	0.0011* (1.7175)	-0.0011* (-1.7983)	0.0011* (1.7175)
<i>Ln(Overall Experience)</i>	-0.0021 (-1.3600)	-0.0031 (-1.6015)	-0.0018 (-0.8158)	-0.0031 (-1.6015)
<i>Ln(Num Firms Covered)</i>	0.0022 (1.0300)	0.0037 (1.5973)	0.0029 (1.0771)	0.0037 (1.5973)
<i>Ln(Num Industries Covered)</i>	0.0014 (0.7571)	0.0024 (1.1637)	0.0015 (0.6495)	0.0024 (1.1637)
<i>Turnover</i>	0.0040** (2.4905)	0.0035* (1.9300)	0.0035* (1.7851)	0.0035* (1.9300)
<i>Return</i>	-0.0027** (-2.4112)	-0.0013 (-1.0503)	-0.0024* (-1.8611)	-0.0013 (-1.0503)
<i>Return Vol</i>	0.1072*** (9.1593)	0.1069*** (8.3860)	0.1101*** (7.7348)	0.1069*** (8.3860)
<i>Size</i>	0.0005 (0.3505)	-0.0018 (-0.9639)	0.0023 (1.2278)	-0.0018 (-0.9639)
<i>ROA</i>	-0.0427*** (-3.1633)	-0.0579*** (-3.9086)	-0.0500*** (-2.9941)	-0.0579*** (-3.9086)
<i>MTB</i>	0.0000 (0.4791)	0.0000 (0.1227)	0.0001 (1.2323)	0.0000 (0.1227)
<i>Instown</i>	0.0086*** (2.8388)	0.0086** (2.4842)	0.0068* (1.8288)	0.0086** (2.4842)
<i>Ln(Firm Age)</i>	0.0181*** (4.8270)	0.0124*** (2.5839)	0.0091** (1.9810)	0.0124*** (2.5839)
<i>Ln(Num Analyst Following)</i>	0.0424*** (17.8889)	0.0447*** (15.7144)	0.0363*** (13.0730)	0.0447*** (15.7144)
Observations	272,096	254,360	182,144	254,360
Adjusted R-squared	0.2088	0.2231	0.2061	0.2231
Analyst FEs	Yes	No	Yes	No
Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	No	Yes	No
Analyst-Firm FEs	No	Yes	No	Yes
Cluster	Analyst	Analyst	Analyst	Analyst

This table presents results from estimating Eq. (3) using OLS. In Panel A, we identify Sustainability Focused Analysts based on all sustainability related questions that they ask. In Panel B, we identify Material Sustainability Focused analysts by limiting the Sustainability questions to only material topics according to SASB's SICS[®]. In Panel C, we focus on Financial Impact Sustainability Focused Analysts, who ask about a sustainability issue in the context of its financial impact on the firm. In Columns (1) and (3) of all panels Analyst, Firm, and Year fixed effects are included individually. In columns (2) and (4) of all three panels, combined Analyst-Firm and Year fixed effects are included. In columns (1) and (2) of all panels, we include both participating and non-participating analysts in the analyses. In columns (3) and (4) of all panels we only include participating analysts in the analyses. t-statistics appear in parentheses and are clustered by analyst. *, **, and *** indicate statistical significance (two-sided) at the 0.1, 0.05, and 0.01 levels, respectively. All variables are defined in Appendix B.

Table 5. Sustainability-Focused Analysts and Relative Forecast Accuracy by Sustainability Dimension

Panel A: Sustainability Focused Analysts					
Dependent Variable= Sustainability Dimension=	<i>Relative Forecast Accuracy</i>				
	Environment	Social Capital	Human Capital	Business Model and Innovation	Leadership and Governance
	(1)	(2)	(3)	(4)	(5)
<i>Sustainability Focused Analyst</i>	0.0085* (1.6830)	0.0113* (1.6596)	0.0137*** (2.6818)	0.0180*** (8.8418)	0.0130*** (8.7551)
Observations	254,360	254,360	254,360	254,360	254,360
Adjusted R-squared	0.2225	0.2225	0.2225	0.2228	0.2228
Controls	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst
Panel B: SASB Material Sustainability Focused Analysts					
Dependent Variable= Sustainability Dimension=	<i>Relative Forecast Accuracy</i>				
	Environment	Social Capital	Human Capital	Business Model and Innovation	Leadership and Governance
	(1)	(2)	(3)	(4)	(5)
<i>Material Sustainability Focused Analyst</i>	0.0174*** (9.0704)	0.0169** (2.1005)	0.0122 (1.5259)	0.0184*** (7.0751)	0.0173*** (5.8909)
Observations	254,360	254,360	254,360	254,360	254,360
Adjusted R-squared	0.2228	0.2225	0.2225	0.2226	0.2226
Controls	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst

Table 5. (Continued)

Panel C: Financial Impact Sustainability Focused Analysts					
Dependent Variable= Sustainability Dimension=	<i>Relative Forecast Accuracy</i>				
	Environment	Social Capital	Human Capital	Business Model and Innovation	Leadership and Governance
	(1)	(2)	(3)	(4)	(5)
<i>Financial Impact Sustainability Focused Analyst</i>	0.0133 (0.8938)	0.0543** (2.3316)	-0.0064 (-0.4477)	0.0141*** (2.9279)	0.0145*** (5.5792)
Observations	254,360	254,360	254,360	254,360	254,360
Adjusted R-squared	0.2225	0.2225	0.2225	0.2225	0.2226
Controls	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst

This table presents results from estimating Eq. (3) using OLS, identifying analyst's specific Sustainability focus based on SASB's five sustainability dimensions. In Panel A we identify Sustainability Focused Analysts based on all sustainability related questions corresponding to a specific dimension. In Panel B, we focus on those Sustainability Focused Analysts who ask about a sustainability issue in the context of its financial impact on the firm. In Panel C we identify Material Sustainability Focused Analysts by limiting the each dimension's Sustainability questions to only material topics according to SASB's SICS®. We include both participating and non-participating analysts in all analyses. All models include the two-way Analyst-Firm and Year fixed effects. t-statistics appear in parentheses and are clustered by analyst. *, **, and *** indicate statistical significance (two-sided) at the 0.1, 0.05, and 0.01 levels, respectively. All variables are defined in Appendix B.

Table 6. Market Reaction to Sustainability-focused Analysts' Forecast Revisions

Dependent Variable=	Three-Day CAR						
	Analyst=	ESG Focused Analyst		Material ESG Focused Analyst		Financial Impact ESG Focused Analyst	
		(1)	(2)	(3)	(4)	(5)	(6)
<i>Revision</i> × <i>Analyst</i>		0.0299*** (2.9309)	0.0420*** (3.3369)	0.0953*** (4.7291)	0.1248*** (5.2447)	0.0394** (2.2323)	0.0585*** (2.8354)
<i>Revision</i>		0.0535*** (10.6538)	0.0549*** (9.0067)	0.0558*** (11.7820)	0.0583*** (10.0749)	0.0578*** (12.0322)	0.0606*** (10.3835)
<i>Analyst</i>		0.0000 (0.0665)	0.0004 (0.7897)	0.0007 (1.1615)	0.0006 (0.8088)	-0.0004 (-0.6409)	-0.0003 (-0.3649)
<i>Horizon</i>		-0.0000*** (-4.5499)	-0.0000*** (-3.4193)	-0.0000*** (-4.4924)	-0.0000*** (-3.4210)	-0.0000*** (-4.5769)	-0.0000*** (-3.5075)
<i>Ln(Brokerage Size)</i>		0.0005 (1.3746)	0.0001 (0.1516)	0.0005 (1.3637)	0.0001 (0.1584)	0.0005 (1.3920)	0.0001 (0.1734)
<i>Ln(Firm Specific Experience)</i>		0.0001 (0.3093)	0.0005 (1.2697)	0.0000 (0.2330)	0.0005 (1.2686)	0.0001 (0.3246)	0.0005 (1.3137)
<i>Ln(Experience)</i>		0.0006 (1.0598)	-0.0001 (-0.1260)	0.0006 (1.0792)	-0.0001 (-0.1091)	0.0006 (1.0536)	-0.0001 (-0.1351)
<i>Ln(No of Firms Covered)</i>		0.0010 (1.3708)	0.0010 (1.1816)	0.0010 (1.3343)	0.0010 (1.1803)	0.0010 (1.3604)	0.0010 (1.2003)
<i>Ln(No of Industries Covered)</i>		0.0000 (0.0196)	0.0004 (0.5420)	0.0000 (0.0193)	0.0004 (0.5336)	0.0000 (0.0204)	0.0004 (0.5369)
<i>Turnover</i>		0.0012* (1.8845)	0.0012 (1.5918)	0.0012* (1.8839)	0.0012 (1.5742)	0.0012* (1.8713)	0.0012 (1.5781)
<i>Return</i>		-0.0137*** (-30.4605)	-0.0138*** (-27.0349)	-0.0137*** (-30.4702)	-0.0138*** (-27.0469)	-0.0137*** (-30.4161)	-0.0138*** (-26.9847)
<i>Return Vol</i>		0.0121** (2.4820)	0.0174*** (3.0962)	0.0121** (2.4770)	0.0175*** (3.1030)	0.0120** (2.4724)	0.0174*** (3.0851)
<i>Size</i>		-0.0028*** (-5.3442)	-0.0037*** (-5.5039)	-0.0028*** (-5.3091)	-0.0037*** (-5.4166)	-0.0028*** (-5.3205)	-0.0037*** (-5.4687)
<i>ROA</i>		0.0728*** (13.6836)	0.0691*** (10.8622)	0.0724*** (13.6261)	0.0687*** (10.8075)	0.0728*** (13.6975)	0.0691*** (10.8742)
<i>MTB</i>		0.0002*** (8.7469)	0.0002*** (7.0630)	0.0002*** (8.7333)	0.0002*** (7.0581)	0.0002*** (8.7410)	0.0002*** (7.0677)
<i>Instown</i>		0.0022* (1.9492)	0.0024* (1.8242)	0.0022** (1.9672)	0.0024* (1.8342)	0.0022** (1.9824)	0.0025* (1.8624)
<i>Ln(Firm Age)</i>		0.0010 (0.7315)	0.0018 (0.9969)	0.0010 (0.7397)	0.0018 (0.9896)	0.0010 (0.7191)	0.0018 (0.9790)
<i>Ln(Num Analyst Following)</i>		-0.0053*** (-6.8351)	-0.0051*** (-5.4109)	-0.0053*** (-6.8543)	-0.0052*** (-5.4771)	-0.0053*** (-6.8362)	-0.0052*** (-5.4247)
Observations		218,355	199,270	218,355	199,270	218,355	199,270
Adjusted R-squared		0.0503	0.0456	0.0504	0.0458	0.0503	0.0456
Analyst FEs		Yes	No	Yes	No	Yes	No
Year FEs		Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs		Yes	No	Yes	No	Yes	No
Analyst-Firm FEs		No	Yes	No	Yes	No	Yes
Cluster		Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

This table presents results from estimating Eq. (4) using OLS. Columns (1), (3), and (5) Analyst, Firm, and Year fixed effects are included individually. In columns (2), (4), and (6) the two-way Analyst-Firm and Year fixed effects are included. In columns (1) and (2), we identify Sustainability Focused Analysts based on all sustainability related questions corresponding to a specific dimension. In columns (3) and (4) we identify Material Sustainability Focused Analysts by limiting each dimension's Sustainability questions to only material topics according to SASB's SICs[®]. In columns (5) and (6), we focus on those Sustainability Focused Analysts who ask about a sustainability issue in the context of its financial impact on the firm. We include both participating and non-participating analysts in all analyses. t-statistics appear in parentheses and are clustered by analyst. *, **, and *** indicate statistical significance (two-sided) at the 0.1, 0.05, and 0.01 levels, respectively. All variables are defined in Appendix B.

Table 7. Cross-Sectional Tests

Dependent Variable= Cross-sectional variable=	<i>Relative Forecast Accuracy</i>			
	<i>Experienced Analyst</i>	<i>Small Firm</i>	<i>Growth Firm</i>	<i>Voluntary ESG Report</i>
	(1)	(2)	(3)	(4)
<i>ESG Focused Analyst × Cross-Sectional Variable</i>	0.0051* (1.7458)	0.0078** (2.1659)	0.0086*** (3.4010)	0.0007 (0.1858)
<i>ESG Focused Analyst</i>	0.0143*** (8.4173)	0.0142*** (9.4858)	0.0125*** (7.2122)	0.0157*** (10.5244)
<i>Cross-Sectional Variable</i>	-0.0004 (-0.1282)	0.0046 (1.2273)	-0.0030* (-1.8380)	-0.0020 (-1.0084)
Observations	254,360	254,360	254,360	254,360
Adjusted R-squared	0.2230	0.2231	0.2231	0.2230
Controls	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes
Cluster	Analyst	Analyst	Analyst	Analyst

This table presents results from estimating Eq. (6) using OLS using multiple cross-sectional variables. In column (1), the cross-sectional variable is an indicator that is equal to 1 when analysts' overall experience is in the year-specific top tercile of our sample, and zero otherwise. In column (2) the cross-sectional variable is an indicator that is equal to 1 when firm size is in the year-specific bottom tercile of our sample, and zero otherwise. In column (3) the cross-sectional variable is an indicator that is equal to 1 when firm's market-to-book-ratio is in the year-specific top tercile of our sample, and zero otherwise. In column (4) the cross-sectional variable is an indicator that is equal to 1 when the firm issued a voluntary ESG report in the year before the analyst issue their forecast, and zero otherwise. All models include the two-way Analyst-Firm and Year fixed effects. We include both participating and non-participating analysts in all analyses. t-statistics appear in parentheses and are clustered by firm and date. t-statistics appear in parentheses and are clustered by analyst. *, **, and *** indicate statistical significance (two-sided) at the 0.1, 0.05, and 0.01 levels, respectively. All variables are defined in Appendix B.

Table 8. Robustness Tests

Panel A: Controlling for firms' voluntary Sustainability report	
Dependent Variable=	<i>Relative Forecast Accuracy</i>
<i>Sustainability Focused Analyst</i>	0.0158*** (11.2461)
<i>Voluntary Sustainability Report</i>	-0.0018 (-0.9869)
Observations	254,360
Adjusted R-squared	0.2230
Controls	Yes
Year FEs	Yes
Analyst-Firm FEs	Yes
Cluster	Analyst
Panel B: Controlling for analysts' number and length of questions	
Dependent Variable=	<i>Relative Forecast Accuracy</i>
<i>Sustainability Focused Analyst</i>	0.0146*** (10.1037)
<i>Ln(Num Analyst Questions)</i>	0.0005 (0.3272)
<i>Ln(Length Analyst Questions)</i>	0.0007 (1.0903)
Observations	254,360
Adjusted R-squared	0.2231
Controls	Yes
Year FEs	Yes
Analyst-Firm FEs	Yes
Cluster	Analyst
Panel C: Excluding "Competitive Behavior" from sustainability topics	
Dependent Variable=	<i>Relative Forecast Accuracy</i>
<i>Sustainability Focused Analyst</i>	0.0153*** (10.1584)
Observations	254,360
Adjusted R-squared	0.2229
Controls	Yes
Year FEs	Yes
Analyst-Firm FEs	Yes
Cluster	Analyst

Table 8. (Continued)

Panel D: Relative forecast accuracy measured based on Hirshleifer et al. (2019)	
Dependent Variable=	<i>Relative Forecast Accuracy HLLT</i>
<i>Sustainability Focused Analyst</i>	0.0916*** (15.5181)
Observations	245,515
Adjusted R-squared	0.0799
Controls	Yes
Year FEs	Yes
Analyst-Firm FEs	Yes
Cluster	Analyst
Panel E: Forecast accuracy measured based on Clement (1999)	
Dependent Variable=	<i>Forecast Accuracy Clement</i>
<i>Sustainability Focused Analyst</i>	0.0419*** (11.6534)
Observations	272,096
Adjusted R-squared	0.1081
Controls	Analyst-level controls demeaned
Year FEs	No
Analyst-Firm FEs	No
Cluster	Analyst
Panel F: Number of sustainability focused questions as test variable	
	<i>Relative Forecast Accuracy</i>
<i>Num Sustainability Focused Questions</i>	0.0057*** (9.7537)
Observations	254,360
Adjusted R-squared	0.2229
Controls	Yes
Year FEs	Yes
Analyst-Firm FEs	Yes
Cluster	Analyst

Table 8. (Continued)

Panel G: Two-year forecast horizon	
Dependent Variable=	<i>Relative Forecast Accuracy</i>
<i>Sustainability Focused Analyst</i>	0.0034** (2.3748)
Observations	248,252
Adjusted R-squared	0.0913
Controls	Yes
Year FEs	Yes
Analyst-Firm FEs	Yes
Cluster	Analyst
Panel H: Controlling for ESG incidents	
Dependent Variable=	<i>Relative Forecast Accuracy</i>
<i>Sustainability Focused Analyst</i>	0.0079*** (5.4068)
<i>ESG Incidents</i>	0.0014 (0.8566)
Observations	254,360
Adjusted R-squared	0.2011
Controls	Yes
Year FEs	Yes
Analyst-Firm FEs	Yes
Cluster	Analyst

This table presents robustness tests from estimating Eq. (3) using OLS. In Panel A, we control for firms' issuance of voluntary sustainability reports. In Panel B, we control for the number of questions and the length of questions that the analyst asks during conference calls. In Panel C, we exclude analysts' sustainability questions regarding "Competitive Behavior". In Panel D, we use an alternative measure for analysts' forecast accuracy based on [Hirshleifer et al. \(2019\)](#). In Panel E, we use the approach used in [Clement \(1999\)](#). In Panel F, we use the number of sustainability-focused questions asked by an analyst one year before issuing their forecast as the test variable. In Panel G, we replicate the analyses for alternative horizons of two-year ahead forecasts. In panel H, we control for the number of ESG incidents of the firm during the fiscal year. In all panels, both participating and non-participating analysts are included in the analysis. All models include combined Analyst-Firm and Year fixed effects are included. t-statistics appear in parentheses and are clustered by analyst. *, **, and *** indicate statistical significance (two-sided) at the 0.1, 0.05, and 0.01 levels, respectively. All variables are defined in Appendix B.

Table 9. Determinants of Analysts' Sustainability Focus

Dependent Variable=	<i>ESG Focused Analyst</i>			<i>Material ESG Focused Analyst</i>			<i>Financial Impact ESG Focused Analyst</i>		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Ln(Brokerage Size)</i>	-0.0041 (-0.8421)	-0.0058 (-1.1773)	0.0034 (0.5852)	-0.0032 (-1.0333)	-0.0034 (-1.1071)	0.0013 (0.3913)	-0.0012 (-0.5785)	-0.0017 (-0.8303)	0.0007 (0.2535)
<i>Ln(Firm Specific Experience)</i>	0.0259*** (11.3036)	0.0257*** (11.2267)	0.0528*** (7.2702)	0.0105*** (6.1017)	0.0103*** (5.9699)	0.0200*** (4.1668)	0.0082*** (6.6822)	0.0082*** (6.6583)	0.0091** (2.4030)
<i>Ln(Overall Experience)</i>	0.0332*** (4.7830)	0.0181* (1.7838)	0.0187 (1.4159)	0.0307*** (6.7496)	0.0145** (2.2653)	0.0097 (1.0907)	0.0026 (0.8141)	0.0125*** (2.7038)	0.0095 (1.4674)
<i>Ln(Num Firms Covered)</i>	0.0370*** (4.4093)	0.0375*** (4.4927)	0.0347*** (3.8148)	0.0108** (1.9405)	0.0102* (1.8344)	0.0062 (1.0725)	0.0033 (0.8383)	0.0027 (0.6785)	0.0012 (0.2571)
<i>Ln(Num Industries Covered)</i>	0.0070 (1.0389)	0.0041 (0.6060)	0.0054 (0.7620)	-0.0019 (-0.4099)	-0.0024 (-0.5290)	0.0033 (0.6962)	0.0014 (0.4333)	0.0018 (0.5546)	0.0032 (0.8371)
<i>Turnover</i>	0.0034 (0.8947)	0.0040 (1.0298)	0.0044 (0.7525)	-0.0021 (-0.7764)	-0.0011 (-0.3792)	-0.0090** (-2.2759)	-0.0017 (-0.8362)	-0.0013 (-0.6643)	-0.0002 (-0.0474)
<i>Return</i>	-0.0054* (-1.7494)	-0.0075** (-2.3789)	-0.0058 (-1.5641)	0.0019 (0.8406)	0.0011 (0.4868)	-0.0001 (-0.0385)	-0.0056*** (-3.2941)	-0.0067*** (-3.8455)	-0.0044** (-2.1344)
<i>Return Vol</i>	-0.1633*** (-5.3669)	-0.0947*** (-2.9312)	0.0733* (1.7886)	-0.0696*** (-3.3852)	-0.0599*** (-2.7082)	0.0164 (0.5804)	-0.0079 (-0.4897)	0.0062 (0.3560)	0.0490** (2.1673)
<i>Size</i>	-0.0239*** (-15.6741)	-0.0227*** (-14.8013)	-0.0258*** (-4.6940)	-0.0131*** (-11.5825)	-0.0130*** (-11.4079)	-0.0115*** (-2.8734)	-0.0044*** (-5.3152)	-0.0039*** (-4.6310)	-0.0083*** (-2.6669)
<i>ROA</i>	0.0129 (0.4068)	0.0422 (1.3363)	-0.0850** (-2.0541)	0.0183 (0.7680)	0.0289 (1.2126)	-0.0216 (-0.7423)	0.0472*** (2.6745)	0.0523*** (2.9641)	-0.0277 (-1.1722)
<i>MTB</i>	-0.0004** (-2.2913)	-0.0004** (-2.4094)	-0.0002 (-0.8693)	-0.0000 (-0.0289)	-0.0000 (-0.4118)	-0.0002 (-1.4322)	-0.0001 (-1.4423)	-0.0001 (-1.1439)	0.0000 (0.1489)
<i>Instown</i>	-0.0044 (-0.6453)	-0.0018 (-0.2573)	-0.0126 (-0.9109)	-0.0092* (-1.8487)	-0.0092* (-1.8257)	-0.0145 (-1.5475)	-0.0083** (-2.0719)	-0.0070* (-1.7214)	-0.0008 (-0.0996)
<i>Ln(Num Analyst Following)</i>	-0.0753*** (-19.3569)	-0.0774*** (-19.7915)	-0.0142* (-1.6939)	-0.0250*** (-8.2710)	-0.0255*** (-8.4169)	-0.0064 (-1.0840)	-0.0324*** (-14.2623)	-0.0336*** (-14.6264)	-0.0102** (-2.0492)
<i>Voluntary ESG Report</i>	0.0055 (1.3733)	0.0044 (1.0877)	0.0064 (1.2863)	0.0057* (1.9425)	0.0048 (1.6198)	0.0001 (0.0212)	-0.0033* (-1.6494)	-0.0029 (-1.4524)	-0.0037 (-1.3559)
Observations	137,454	137,454	125,439	137,453	137,453	125,439	137,454	137,454	125,439
Adjusted R-squared	0.1156	0.1171	0.1882	0.0966	0.0975	0.1938	0.0522	0.0526	0.1068
Analyst FEs	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year FEs	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Analyst-Firm FEs	No	No	Yes	No	No	Yes	No	No	Yes
Cluster	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst	Analyst

This table presents results from estimating Eq. (8) using OLS. In columns (1)–(3) the dependent variable is Sustainability Focused Analyst, in columns (4)–(6) the dependent variable is Financial Impact Sustainability Focused Analyst who ask sustainability questions in the context of its financial impact on the firm, and in columns (7)–(9) the dependent variable is Material Sustainability Focused Analyst. In columns (1), (4), and (7) analyst characteristics, firm characteristics, and analyst fixed effects are included. In columns (2), (5) and (8) analyst characteristics, firm characteristics, analyst, and year fixed effects are included. In columns (3), (6), and (9) analyst characteristics, firm characteristics, analyst, firm, and year fixed effects are included. We include both participating and non-participating analysts in all analyses. t-statistics appear in parentheses and are clustered by analyst. *, **, and *** indicate statistical significance (two-sided) at the 0.1, 0.05, and 0.01 levels, respectively. All variables are defined in Appendix B.