

Broker In-House ESG Research

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ABSTRACT: This study examines the determinants and consequences of broker in-house ESG research. Using manually collected brokerage ESG research data, we find that the provision of in-house ESG research is positively related to both demand-side factors (client demand, internal demand, and local ESG awareness) and supply-side factors (broker size and coverage of sustainable industries). Regarding the consequences of such research, we find that in-house ESG research is associated with improved earnings forecast accuracy in industries where ESG is more salient. Further, the market reaction to earnings forecast revisions is stronger when equity analysts have access to in-house ESG research. Finally, we observe a consistent pattern suggesting that ESG analysts support equity analysts beyond forecast accuracy, as equity analysts with access to in-house ESG research issue more accurate target prices, more informative recommendation upgrades for ESG-heavy industries, and discuss ESG issues more extensively in their analyst reports.

Data Availability Statement: The data used in this study are obtained from publicly available sources identified in the paper, as well as job posting data licensed from Lightcast. Sample construction procedures are described in the paper. Researchers interested in the job posting data should contact Lightcast directly, as access is subject to licensing restrictions.

JEL Classifications: G14; G24; M41; M14.

Keywords: environmental, social, and governance (ESG); corporate social responsibility; brokerage research; sell-side analysts.

We thank Urooj Khan (editor) and two anonymous reviewers for their helpful comments and suggestions throughout the review process. Their feedback substantially improved the paper. We also thank Chris Akroyd, Borhan Bhuiyan, Limei Che, Chen Chen, Peter Clarkson, Sturla Fjesme, Adrian France, Ping Gong, Harrison Guo, Julie Harrison, David Hay, Gladys Lee, Xiaoxia Li, Xingchen Lin, Bo Liu, Louise Lu, Diandian Ma, Knut Nygaard, Kizkitza Pastor, Johan Reindt, Tom Scott, ThuPhuong Truong, Christophe van Linden, Rencheng Wang, Mark Wilson, Ava Wu, Yuhao Xuan, Alex Yang, Dan Zhang, David Zhao, Mei Zhao, Hui Zhou, and seminar participants at Dongbei University of Finance and Economics, Guangdong University of Technology, Indian Institute of Management Jammu, Northeastern University (China), Oslo Metropolitan University, Sun Yat-sen University, The University of Auckland, Australasian Early Career Researchers Support Network, 2022 Auckland Region Accounting Conference, 2023 Accounting and Finance Association of Australia and New Zealand Annual Conference, 2023 New Zealand Quantitative Accounting Research Symposium, and 2024 Contemporary Accounting Research Insights Forum for their helpful comments. We gratefully acknowledge the financial support from The University of Auckland Business School and The Australian National University.

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Supplemental material is available online, as linked in the text.

Any use of generative artificial intelligence (AI) or AI tools by the authors has been disclosed in the “[Declaration of Generative AI and AI-Assisted Technologies](#)” section.

Editor’s note: Accepted by Urooj Khan, under the Senior Editorship of Kathryn Kadous.

Submitted: July 2023
Accepted: July 2026
Early Access: August 2026

I. INTRODUCTION

A voluminous body of literature examines sell-side analysts (Bradshaw, Ertimur, and O'Brien 2017; Ramnath, Rock, and Shane 2008) but mostly focuses on equity analysts and their research outputs, such as earnings forecasts and stock recommendations. In fact, brokerage research includes more than equity research. For example, Goldman Sachs provides in-house sustainability research, economic research, and portfolio research in addition to equity research.¹ Industry groups and investors recognize the value of these other types of brokerage research and present awards for outstanding brokerage research in these areas every year (e.g., *Institutional Investor*, *Investment Week*, and *Extel Survey*). Recent research has also started to examine the value of specialist brokerage research services beyond equity research, including in-house macroeconomic analysts, Washington policy analysts, and quantitative analysts (Birru, Gokkaya, Liu, and Markov 2024; Bradley, Gokkaya, Liu, and Michaely 2024; Hugon, Kumar, and Lin 2016).

In this paper, we study broker in-house environmental, social, and governance (ESG) research, which has not been comprehensively examined despite being available since the early 2000s. One reason for the limited research on brokerage ESG research could be the lack of brokerage ESG research data, which makes it difficult to determine whether and when a brokerage house initiated in-house ESG research. We manually search and collect data on ESG analysts who worked at brokerage houses from LinkedIn.com, the largest professional networking service.² Based on these data, we identify brokerage houses with ESG analysts and determine the earliest year in which an ESG analyst appears. By 2021, we find 73 unique ESG analysts employed by 23 of 287 U.S.-based brokerage houses, with most of the growth occurring since 2017. We begin by providing descriptive evidence regarding the number and background of ESG analysts. We then examine two novel research questions: (1) what factors are associated with a broker's decision to provide in-house ESG research and (2) how in-house ESG research affects the quality of equity research produced by that broker's equity analysts.

Prior studies rarely examine the determinants related to the provision of specific brokerage services. Existing studies on specialist brokerage research services focus primarily on the consequences of such services (Birru et al. 2024; Bradley et al. 2024; Hugon et al. 2016). Green, Jame, Markov, and Subasi (2014) consider the determinants of broker-hosted investor conferences. They focus on how a firm's characteristics influence attendance at its investor conferences, thereby adopting a firm-level perspective. In contrast, we conduct a brokerage-level analysis. Specifically, we construct a determinants model based on economic factors that are likely to affect the demand for and supply of ESG research at brokerage houses in the U.S.

On the demand side, we expect that a broker's decision to provide in-house ESG research will be related to clients' demand for ESG investments, internal demand from the broker's equity analysts, and ESG awareness in the broker's locality. Regarding the supply side, we predict that larger brokers, brokers with green bond underwriting, and brokers covering sustainable thematic industries, such as clean energy, will be more likely to provide in-house ESG research, because these brokers have greater resources, a strategic interest in the ESG market, and expertise in ESG issues. Aside from brokers' involvement in green bond underwriting, we find evidence to support these expectations.

In terms of the consequences of ESG research, prior literature has documented that ESG information is useful for equity research (Bernardi and Stark 2018; Dhaliwal, Radhakrishnan, Tsang, and Yang 2012; Muslu, Mutlu, Radhakrishnan, and Tsang 2019). ESG analysts possess relevant expertise and insights that can improve the quality of equity research. Several studies on financial analysts highlight the positive effects of the analysts' colleagues on their research outcomes (Bradley, Gokkaya, and Liu 2019; Groyberg and Lee 2008; Hugon et al. 2016). We posit that in-house ESG research enhances equity research in several ways. First, ESG analysts cooperate with equity analysts to integrate ESG information into equity research. Even though equity analysts may have access to third-party ESG ratings, these ratings can vary substantially between raters (Berg, Kölbel, and Rigobon 2022; Chatterji, Durand, Levine, and Touboul 2016; Christensen, Serafeim, and Sikochi 2022) and can be difficult for equity analysts to integrate into the valuation process (e.g., CFA Institute 2018; Ashwell 2021). ESG analysts can provide incremental insights and can help equity analysts better understand the ratings, especially from a forward-looking perspective (Ashwell 2021). Second, ESG analysts produce thematic reports on ESG issues that can provide valuable insights for equity analysts. Third, ESG analysts deliver ESG training to equity analysts, improving their ability to use ESG information. Fourth,

¹ Goldman Sachs website: <https://www.goldmansachs.com/careers/divisions/global-investment-research/> (last accessed August 14, 2024).

² We identify ESG analysts' job responsibilities through their job descriptions and broker's website. Other analyst studies using LinkedIn data include Bradley, Gokkaya, and Liu (2017a); Bradley, Gokkaya, Liu, and Xie (2017b); Gu, Z. Li, Yang, and G. Li (2019); and Li, Lin, Lu, and Veenstra (2020). To validate our hand-collected LinkedIn data, we use three alternative data sources, i.e., job posting data from Lightcast, analyst ESG reports from Mergent Online Investext, and brokers' websites. As discussed in Section 1 of the Online Appendix, this analysis suggests that our dataset is comprehensive.

ESG analysts can help equity analysts better understand their clients' ESG-related demands, especially those of institutional investors.

Using a sample of equity analysts employed at U.S.-based brokers, we examine the relationship between in-house ESG research and the quality of equity analysts' research outputs. We find that in-house ESG research is associated with higher quality research outputs for equity analysts who cover firms in ESG-heavy industries: environmentally sensitive industries, controversial industries, or industries with more Sustainability Accounting Standards Board (SASB) disclosure topics, consistent with ESG information being more value relevant in these industries. For instance, we find that earnings forecasts issued by analysts at brokers with ESG research are 4.18–6.07 percent more accurate than those issued by analysts at other brokers for firms in ESG-heavy industries. In a dynamic analysis, we find that the improvement starts in the year in-house ESG research is established.

In addition, we conduct three sets of tests to explore the mechanisms through which ESG research enhances earnings forecast accuracy. First, using a cross-sectional approach, we find that access to ESG research is associated with improved forecast accuracy for firms with greater ESG risks and ESG disagreements, for controversial industries, and high SASB disclosure industries, suggesting that ESG research facilitates the interpretation of complex ESG information. Conversely, we observe a substitutive effect between third-party ESG rating coverage and in-house ESG research on forecast accuracy, and this effect is particularly evident in non-ESG-heavy industries. These results suggest ESG research and third-party ratings can serve as substitute sources of information, particularly in contexts where ESG issues are less salient. Second, we investigate analysts' incorporation of ESG news into earnings forecasts. We find that analysts tend to over-react to negative environmental news from environmentally sensitive and controversial industries. However, in-house ESG research alleviates this over-reaction, highlighting its role in facilitating the interpretation of environmental news for these industries.

Third, we consider the implications of ESG research for firms with high or low exposure to social issues. For ESG-heavy industries, the positive association between ESG research and forecast accuracy is not affected by the level of exposure to social issues; however, for non-ESG-heavy industries, we find some evidence that, as exposure to social issues increases, ESG research is associated with lower forecast accuracy. This finding is consistent with the limited attention and information overload theory, which suggests that greater information volume and complexity can impair market participants' judgment due to cognitive constraints (Hirshleifer and Teoh 2003; Chapman, Reiter, White, and Williams 2019). Compared with environmental issues, social issues are more diffuse, context-dependent, and qualitative and less comparable and financially interpretable. Relatedly, the financial consequences of social issues are more volatile and uncertain, with broader exposure to regulatory penalties and lawsuits. These challenges create information frictions and cognitive burden that may impair the integration of social information into equity analysis.

Furthermore, we observe a consistent pattern suggesting that ESG analysts support equity analysts beyond forecast accuracy, as equity analysts with access to in-house ESG research issue more informative earnings forecast revisions, more accurate target prices, more informative recommendation upgrades for ESG-heavy industries, and discuss ESG issues more extensively in their analyst reports.

Overall, the consequence models' results provide evidence that in-house ESG research improves the research quality of equity analysts in industries where ESG matters most. Our finding that the effect of in-house ESG research differs cross-sectionally echoes a CFA survey (CFA Institute 2018), which notes that ESG integration is sector and industry dependent, especially for E and S factors.

Our paper contributes to the literature in several ways. First, the paper provides initial evidence on broker in-house ESG research, a service developed over the last two decades, but not yet comprehensively studied. Our study also adds to a limited but growing literature on brokers' in-house research services beyond equity research (Birru et al. 2024; Bradley et al. 2024; Hugon et al. 2016). Although these studies indicate that these in-house research services can assist brokers' sell-side equity analysts, given the broad scope and qualitative issues associated with ESG, it is unclear whether in-house ESG research would have the same effect.

Second, our study broadly contributes to the equity research literature, particularly to the rapidly growing stream examining how equity analysts evaluate ESG issues. Although prior research provides some evidence that equity analysts consider ESG information (e.g., Cuculiza, Kumar, Xin, and Zhang 2021; Park, Yoon, and Zach 2025), it also highlights that analysts face challenges in incorporating this information. For example, the incorporation of ESG information is incomplete (Addoum, Ng, and Ortiz-Bobea 2023; Chan 2022), and not all equity analysts are equally adept at evaluating ESG information (Faralli 2024). Our study offers new insights into the resources available to equity analysts to support their own analysis, namely, dedicated ESG analysts. In addition, unlike much of the existing literature, which focuses on negative ESG events (e.g., Park et al. 2025) or climate-related issues (e.g., Addoum et al. 2023; Chan 2022; Cuculiza et al. 2021; Faralli 2024), our findings demonstrate that the influence of ESG specialists extends beyond these specific contexts. We also provide an early exploration of social issues in the equity research setting.

Third, to the best of our knowledge, there is little if any evidence on the determinants of brokerage services. We examine the economic determinants of in-house ESG research and provide empirical evidence on how demand-side and supply-side factors influence a broker's provision of ESG research. Our findings provide new insights into several streams of literature. For example, we provide evidence suggesting that brokers cater to buy-side clients by providing ESG research, complementing research on sell-side catering (Chiu, Lourie, Nekrasov, and Teoh 2021; Pacelli 2019).

The remainder of the paper proceeds as follows. Section II provides background information on ESG research. Section III describes our data and key measures. Section IV investigates the determinants of ESG research. Section V explores the effects of ESG research on equity research. Section VI concludes.

II. BACKGROUND

Large brokerage firms, including JP Morgan, UBS, HSBC, and Citigroup, pioneered in-house ESG research in the 2000s. The Enhanced Analytics Initiative (EAI) was launched by buy-side firms and asset owners in 2004 to encourage research into extra-financial issues through commissions, which merged under the Principles for Responsible Investment (PRI) in 2008 to continue supporting ESG research. Brokers' in-house ESG research encompasses multiple dimensions, including thematic, fundamental, and systematic research.³ Thematic research focuses on sustainable and thematic trends, such as demographic change, emerging industries, and technology. Examples include "The Low Carbon Economy" by Goldman Sachs and "Globesity—The Global Fight Against Obesity" by Bank of America Merrill Lynch. Conducting ESG thematic research and publishing reports are important responsibilities of ESG analysts. According to Extel, which awards leading brokerage sustainability research, thematic reviews and ideas are considered the most critical socially responsible investing (SRI)/ESG research service for the buy-side (Extel 2015). Another key dimension of ESG research is fundamental research, which is emphasized by many brokers.⁴ It involves incorporating ESG factors into equity research, including forecasted financials and valuation models (i.e., ESG integration). ESG analysts work collaboratively with equity analysts to support the integration process. The third dimension is systematic analysis, based on quantitative techniques to analyze the relationship between ESG ratings and the performance and valuation of their securities. Some brokerage houses are pioneering the use of machine-learning tools in their ESG research (Acuity 2020). It is important to note that brokerage ESG research is not limited to the abovementioned aspects. Different brokerage houses may focus on different types of ESG research, and their emphasis on ESG research may vary.

As an example, Barclays hired Marie Freier as the global head of cross-asset ESG research in 2021. Freier describes her job scope as "to build a team of ESG experts who can work with Barclays' equity and credit analysts, and to anticipate regulatory and market changes coming down the road" (quoted in Ashwell 2021). Freier's role also involves coordinating the ESG research Barclays has been producing across different parts of the business, including the sustainability team, the quant team, and the fundamental analysts. Freier (quoted in Ashwell 2021) states,

Part of why this role is so difficult is that you're telling very experienced, intelligent folk who have been doing this for a very long time that they haven't been factoring in crucial elements of ESG...We need to challenge ourselves to analyze non-financial and intangible topics, even though they don't fit as neatly into financial analysts' way of working.

Similarly, at Citi, Anita McBain was appointed as the head of Europe, the Middle East, and Africa (EMEA) ESG research in 2020. Prior to this, McBain was the head of responsible investment and ESG at M&G Investments, where she gained experience in ESG integration on the buy side. McBain (quoted in Ashwell 2021) explains,

My mandate here is to raise awareness for ESG, to lead on integration of ESG, to evidence that integration and to demonstrate its outcomes. I believe it's really important to be seen as an enabler. I'm there to support my colleagues and work side by side with them. A lot of our analysts have 25 years of deep sector expertise and in many cases they've been focused on ESG integration already. I'm working to formalize that into a structure.

Despite its two-decade history, brokerage ESG research remains unexplored.⁵ Studies on other types of brokerage in-house research have started to emerge. Hugon et al. (2016) find that in-house macroeconomic research improves the

³ For example, an introduction of ESG research can be found from Barclays' website: https://live.barcap.com/publiccp/RSR/nyfipubs/barcap/researchbrochure/ESG_Brochure.pdf (last accessed August 14, 2024).

⁴ Examples include UBS (<https://www.ubs.com/global/en/investment-bank/what-we-offer/esg.html>) and HSBC (<https://www.research.hsbc.com/C/1/1/323/NVpGvmt>).

⁵ Jemel-Fornetty, Louche, and Bourghelle (2011) is one exception with limited discussion of ESG research, including the emerging trend and institutional mechanisms of integrating ESG into mainstream investment, including sell-side ESG research.

quality of equity research. [Bradley et al. \(2024\)](#) consider in-house Washington policy analysts who monitor political developments and assess the impact of policy changes. They find that sell-side analysts at brokers with a Washington policy analyst issue superior recommendations for firms that are more politically sensitive. [Birru et al. \(2024\)](#) find that analysts who have access to in-house quantitative research issue recommendations that better reflect anomalous cross-sectional return predictability.

Although these studies document the benefits of specialist in-house research, our study is distinct. First, in contrast to macroeconomic analysts and quantitative research analysts, who focus on quantitative economic and market data, ESG analysts primarily deal with qualitative, nonfinancial information related to a broad range of issues from greenhouse gas emissions to modern slavery. Second, in contrast to Washington policy analysts who focus on a specific type of external stakeholder, i.e., the U.S. federal government, ESG analysts confront issues regarding a host of external stakeholders, including customers, suppliers, employees, communities, legislators, regulators, and activists. Third, the role of ESG analysts is a more recent phenomenon. Most U.S.-based ESG analysts have been appointed since 2017. As such, it is not clear whether the results related to other specialist in-house research analysts can be generalized to in-house ESG analysts.

Despite the lack of academic research, investors recognize the value of other types of brokerage research. For example, the 2022 All-America star rankings select star analysts for various types of research, including accounting and tax policy, economics, equity-linked strategies, ESG research, portfolio strategy, quantitative research, technical analysis, and public policy research. To bridge the gap between academic research and industry practice, this paper aims to provide insights into brokerage ESG research from two perspectives: (1) the determinants of ESG research and (2) the potential impacts of in-house ESG research on equity analysts' research outputs.

Although we focus on in-house ESG research, we recognize that an emerging line of research examines how equity analysts evaluate ESG issues. For example, [Park et al. \(2025\)](#) examine whether equity analysts' outputs, i.e., EPS forecasts, recommendation revisions, and target prices, can predict firms' future ESG performance. They find that these outputs are associated with negative ESG events in the following year, consistent with equity analysts incorporating ESG risks in their analyses. [Cuculiza et al. \(2021\)](#) find that equity analysts located in areas where firms are more affected by climate change are more likely to incorporate climate change information into their earnings forecasts and that their earnings forecasts are less optimistic and more accurate. Similarly, [Faralli \(2024\)](#) finds that equity analysts experiencing unexpected weather shocks have lower forecast bias and error, whereas [Addoum et al. \(2023\)](#) find evidence that analysts adjust or partially adjust forecasts to incorporate the effects of temperature extremes.

Although these studies provide some evidence that equity analysts consider ESG information, they also suggest that the incorporation of such information remains incomplete. For example, [Addoum et al. \(2023\)](#) find that analysts are slow to respond to interquarter temperature shocks. Further, [Chan \(2022\)](#) documents that very few analyst reports (less than 1 percent) discuss climate-related topics, although the discussion is informative for firms most exposed to climate change. Also, evidence suggests that not all equity analysts are equally adept at evaluating ESG information. For example, [Faralli \(2024\)](#) finds that high-performance analysts better incorporate climate risks, whereas low-performance analysts tend to be overly pessimistic and over-react to such risks. Although some of these studies focus only on climate-related issues, collectively they suggest that greater guidance may facilitate more timely and complete incorporation of ESG information by equity analysts. In this regard, consistent with the quotes by Marie Freier and Anita McBain above, ESG analysts may help equity analysts better understand the impact of ESG factors. However, whether and how ESG analysts can help (or hurt) the research quality of equity analysts is an empirical question.

III. DATA AND KEY MEASURES

ESG Research Data

We collect brokerage ESG research data from LinkedIn.com.⁶ We begin by obtaining all sell-side equity analysts' recommendations for U.S. firms issued between 2000 and 2021 from the Institutional Brokers Estimate System (I/B/E/S) recommendations file. This yields 16,564 analysts at 1,062 unique I/B/E/S brokers issuing 611,326 recommendations. For these 1,062 brokers, we identify brokerage house names as follows. Starting with the I/B/E/S recommendation files, which provide abbreviations for broker names and analyst names (forename initial and surname), we identify

⁶ Our sample was collected during February 2022. Samples may vary if the data are collected at a different time. To understand whether it is common for ESG analysts to maintain active profiles on LinkedIn, we draw on research studying sell-side analysts' LinkedIn profile information. [Bradley et al. \(2017a\)](#) document 52 percent of identified analysts maintained a LinkedIn profile from 1983 to 2011. [Li, Lin, and Lu \(2023\)](#) report 68 percent of identified sell-side analysts used LinkedIn in 2015. Given that LinkedIn users have grown from 145 million in 2011 to 810 million in 2021, it is expected that the proportion of analysts who use LinkedIn should be even higher in our sample using a more recent period.

analysts and their affiliated brokers using the following sources. First, we search for analysts on BrokerCheck, a website maintained by the Financial Industry Regulatory Authority (FINRA), which contains the employment histories of FINRA-registered securities industry professionals. Second, we search for analysts on LinkedIn. This enables us to identify analysts who work for non-U.S. brokerage houses. Third, we use a list of All-America star analysts from *Institutional Investor* magazine. The list contains the names of star analysts and their brokerage houses. Fourth, we visually compare and check analyst-broker pairs from the abovementioned sources with the names in the I/B/E/S files to identify the brokerage houses. This procedure enables us to identify 550 brokers with 14,566 analysts issuing 578,862 recommendations, accounting for 95 percent of all recommendations in I/B/E/S.

We use LinkedIn.com to search for ESG analysts working at brokerage firms we identified in the I/B/E/S database. We apply the following search criteria: (1) the analyst currently works at the identified broker or had worked at the identified broker; (2) the analyst's job title contains "ESG," "sustainability," or "sustainable"; and (3) the position title contains "research," "analyst," or "associate." We then screen the results and remove records if (1) the company is a buy-side firm, that is, the company name contains "asset management," "wealth management," or "investment management" or the position title contains "buy-side," "buy side," or "portfolio manager"; (2) the analyst holds sustainable finance positions, that is, the position title contains "sustainable finance," "capital market," "sustainable banking," "sustainable dcm," or "bond"; or (3) the analyst holds sector analyst positions (e.g., energy and sustainability sectors).

This process yields 510 unique ESG analysts at 76 unique U.S. and non-U.S. brokerage houses.⁷ We further collect detailed analyst information on employment, education, and certificates from their profiles. Because our analyses examine the research outputs of equity analysts for U.S. firms, we focus on in-house ESG research at U.S. brokers to exclude advantages of local analysts over foreign analysts, such as familiarity with the local market, management access, language proficiency, and regulatory knowledge (Bae, Stulz, and Tan 2008; Comiran and Siriviriyaikul 2019). Our final sample consists of 73 unique ESG analysts with 78 distinct ESG analyst positions at 23 unique U.S. brokerage houses.^{8,9}

Characteristics of ESG Analysts

Table 1 reports the characteristics of ESG analysts at U.S. brokers.¹⁰ We summarize the experience, education, and certificate statistics of the ESG analysts. On average, ESG analysts have 12.06 years of general work experience before they became ESG analysts, suggesting that the position requires a certain level of industry experience. Thirty-five percent of analysts have ESG-related experience, including ESG research, sustainable banking, and sustainable investment. ESG analysts have a mean of 1.68 years of ESG-related experience before their appointment. Eighty-three percent of ESG analysts have research-related experience; for example, some worked as equity analysts covering sustainability-related industries (e.g., green energy). On average, ESG analysts have 5.55 years of research-related experience. Finally, 72 percent of analysts have work experience in the finance industry, with an average of 4.33 years in the sector.¹¹

Education information is available for 47 of the 78 distinct ESG analyst positions. Eighty-one percent of ESG analysts have finance or economics degrees, whereas 28 percent have ESG or sustainability-related degrees. We further present summary statistics for professional licenses and certificates from the 15 ESG analyst positions for which this information is available. Consistent with their educational backgrounds, 93 percent of ESG analysts hold finance-related certificates or licenses.

We also find that in-house ESG research at U.S. brokers is a recent development, especially compared with non-U.S. brokers. As illustrated in Section 2 of the Online Appendix, most of the growth in in-house ESG research in the U.S. has occurred since 2017, and only in 2021 did the U.S. become the country with the most ESG analysts (surpassing the U.K.).

IV. DETERMINANTS OF IN-HOUSE ESG RESEARCH

Related Literature

Prior financial analyst literature mostly focuses on equity research. One strand of literature investigates factors related to equity analysts' efforts and decisions to follow a firm. Bhushan (1989) constructs a model of analyst

⁷ During our sample period, we find no cases where a brokerage house established and then eliminated its in-house ESG function.

⁸ A few analysts have held ESG analyst roles at different brokerage houses.

⁹ We find that, over our sample period, 10 percent of analyst-firm-year observations have access to in-house ESG research. However, by 2021, that percentage increased to 35.15 percent. Importantly, this is similar to the figures reported by Hugon et al. (2016) for in-house macroeconomists. They state that between 27.9 percent and 30.1 percent of their analyst-firm-year observations have access to in-house macroeconomic research (see their Table 2).

¹⁰ We provide similar information for an international sample (i.e., U.S. and non-U.S. ESG analysts) in Section 2 of the Online Appendix.

¹¹ Work experience in the finance industry is defined as work experience in I/B/E/S brokers or other branches within the same financial institution, e.g., RBC Global Asset Management, which is the asset management branch of RBC.

TABLE 1

ESG Analyst Work Experience, Education, and Certificate Summary

Panel A: ESG Analyst Experience Characteristics

No. of ESG analysts	73
No. of ESG analyst positions	78

Type of experience	Mean Years of Experience	Related Experience (#)	Related Experience (%)
General experience	12.06	78	100
ESG-related experience	1.68	27	35
Research experience	5.55	65	83
Finance experience	4.33	56	72

Panel B: ESG Analyst Education Characteristics

No. of observations with education information	47
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	Related Degree (#)	Related Degree (%)
Finance or Economics degrees	38	81
ESG-related degrees	13	28

Panel C: ESG Analyst Certificate Characteristics

No. of observations with certificate information	15
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	Related Certificate (#)	Related Certificate (%)
Finance-related certificates	14	93
Chartered Financial Analyst (CFA)	4	27
ESG-related certificates	4	27

This table summarizes the past work experience, education, and certificate characteristics of 73 unique ESG analysts at 23 unique U.S. brokerage houses in our sample.

following based on firm characteristics that affect the demand for and supply of analyst services. Early research finds that analysts are incentivized to cover and prioritize firms expected to perform well (Das, Guo, and Zhang 2006; Hayes 1998; McNichols and O'Brien 1997). More recent studies find that analyst coverage and effort are related to investment banking business (Bradley, Jordan, and Ritter 2008; Dechow and You 2012; DeGeorge, Derrien, and Womack 2007), trading incentives (Groysberg, Healy, and Maber 2011; Pacelli 2019), and information acquisition costs (Hameed, Morck, Shen, and Yeung 2015; O'Brien and Tan 2015). The evidence shows that analysts weigh the benefits gained from clients against the costs of service provision.

As ESG research and equity research are both research services and share similar client bases, we draw on the equity analyst literature and develop theory and empirical models to examine the economic determinants of ESG research. However, the decision to provide ESG research is more salient and has wider implications than the decision to follow a particular firm. Coverage decisions are made by analysts and approved by the broker's research management (Brown, Call, Clement, and Sharp 2015). An analyst can initiate or terminate coverage with little cost. In contrast, the decision to provide ESG research is made by top management in the research department or brokerage house. Usually, brokerage houses need to hire ESG experts from outside the firm. In our sample, 63 percent of ESG analysts worked for another company before assuming their current roles. Once the ESG research facility is established, the decision to drop it becomes costly because it incurs redundancy and resettlement costs and could adversely affect employee morale and the research department's reputation. Therefore, the decision calculus for providing in-

house ESG research is likely more complex than an analyst's coverage decision. Furthermore, coverage decisions are more likely to be firm- and analyst-specific, whereas the provision of ESG research may be driven by industry-wide, macroeconomic, or brokerage-level factors.

Research Design

In developing the determinants model, we follow Bhushan's (1989) framework and consider the demand for and supply of an economic phenomenon. Specific to our research setting, we propose several brokerage-level factors that could influence demand for or supply of broker ESG research.

Factors Related to the Demand for In-House ESG Research

First, we consider client demand for ESG investing. As investors increasingly incorporate ESG information into their investment decisions, financial professionals indicate that client demand is a major driver of ESG integration (Amel-Zadeh and Serafeim 2018; CFA Institute 2018, 2019). Although the influence between supply and demand for ESG research can be two-way, it is more likely to be from asset owners to the buy-side and sell-side. According to a survey by Acuiti (2020), only 26 percent of buy-side respondents believe the sell-side is advancing ESG at the same pace as their own, suggesting that buy-side demand drives sell-side ESG service provision. Similarly, in our sample, we observe that some banks established their buy-side ESG research earlier than their sell-side ESG research. For instance, UBS Global Asset Management's first ESG research position in our sample is a sustainability analyst starting in 2001, whereas UBS established its ESG team and appointed its first sell-side ESG analyst in 2004.¹² Consistent with the survey evidence and empirical observations, we hypothesize that brokers are more likely to provide ESG research when client demand is higher.

We proxy client demand using the size of sustainable investment funds in the city where the broker's office is located ($SI\ Fund_{kt}$). We first obtain the sustainable investment characteristics from Morningstar Direct. As per Morningstar, funds are defined as sustainable if they fall into one of three categories: (1) ESG fund, which incorporates ESG principles into the investment process; (2) impact fund, which seeks to make an impact with investments on specific issue areas, such as gender diversity; or (3) environmental sector fund, which invests in environmentally oriented industries, such as renewable energy or water. We then calculate the logarithm fund size of all sustainable investment funds in broker k 's city for year t .¹³

Second, demand for ESG research may stem internally from equity analysts. Equity analysts with a more favorable attitude toward ESG are more likely to integrate ESG factors into research and valuation, thereby increasing the internal demand for ESG research. We use the value-weighted average ESG performance of firms covered by broker k 's portfolio ($ESGP_{kt}$) as a proxy for the equity research team's overall attitude toward ESG. In addition, equity analysts may require ESG research to better integrate ESG-related risks. We measure this demand using the volatility of portfolio ESG performance ($ESGP\ Vol_{kt}$) calculated over the three most recent years. As higher ESG performance volatility reflects greater ESG-related risks, *ceteris paribus*, ESG integration is more relevant for firms with high ESGP volatility. As such, we expect a positive relationship between $ESGP\ Vol$ and the provision of ESG research.

Third, local ESG awareness could increase demand for in-house ESG research. Investors and asset owners in states with higher ESG awareness are more likely to integrate ESG considerations in investment strategies, thereby driving increased demand for ESG investment. Similarly, equity analysts in these states may be more inclined to incorporate ESG factors into their research, stimulating internal demand for ESG research.

Our measure of local ESG awareness is an indicator of state climate adaptation plans ($Climate_{kt}$), which are state-led plans designed to prepare for the impacts of climate change in the U.S. Following Ray and Grannis (2015), who document significant variation in the development of these plans across states, we obtain state-level adaptation plans and their finalization dates from Georgetown Climate Center (GCC) for the period 2008–2021.¹⁴ We construct $Climate_{kt}$ as an indicator variable that equals 1 if broker k 's office is located in a state that has finalized climate adaptation plans in year t and 0 otherwise.

¹² UBS' first ESG analyst, Julie Hudson, started to work as an ESG analyst since December 2004. In her LinkedIn profile (<https://uk.linkedin.com/in/julie-hudson-3309b811>), she mentioned that "April 2022 was the 17-year anniversary of the UBS ESG team's first publication."

¹³ Morningstar (2021) provides fund's sustainable investment characteristics from 2018. We retrospect the sustainable investment characteristics using the earliest data available. One limitation of this method is it does not consider that some funds may repurpose as a sustainable investment fund after the inception date. However, this could be uncommon. According to a report by Morningstar on U.S. sustainable funds, only 11 out of 534 funds repurposed to ESG before 2018. In robustness tests, we use a sample from 2018, and it does not change our inference of the impact of sustainable funds on ESG research.

¹⁴ State adaptation progress can be extracted from <https://www.georgetownclimate.org/adaptation/plans.html>

Factors Related to the Supply of In-House ESG Research

For supply-side factors, we start with brokerage house size ($Bkr\ Size_{kt}$) measured by the number of analysts. Since larger brokerage houses have larger client bases, the cost of providing ESG research per client is lower due to economies of scale. With more resources and lower marginal costs, larger firms are more likely to offer ESG research, as the benefits (e.g., increased trading commissions and better reputation) are expected to outweigh the costs.

The second factor we consider is green bond underwriting. Brokers that underwrite green bonds may have a strategic interest in the ESG market or their top management may have a positive view of ESG-related services. We expect brokers with green bond underwriting services to be more likely to provide ESG research. We identify green bond underwriting from SDC Platinum by filtering bond issuances with green bonds listed in the use of proceeds. We create a green bond indicator ($Green\ Bonds_{kt}$), which equals 1 if broker k is a green bond underwriter in year t .¹⁵

Next, we consider whether a broker covers sustainable thematic industries. We observe that a subset of ESG analysts comprises former equity analysts who previously covered sustainable thematic industries, such as green energy. ESG analysts and equity analysts covering these industries may share common knowledge and skill sets, which likely reduces the costs associated with establishing a dedicated ESG research team. As such, we expect brokers covering sustainability-oriented industries to be more likely to provide ESG research. We collect the percentage of sustainable thematic revenues among firms covered by brokers from Morningstar Direct. We create a sustainable thematic coverage dummy ($Sustain\ Theme_{kt}$), which equals 1 if broker k follows firms that generate sustainable thematic revenues in year t .¹⁶

In addition to the abovementioned factors, we control for average firm characteristics within a broker's portfolio and average analyst characteristics that may affect its decision to provide ESG research. Specifically, we include average firm size ($Avg\ Size_{kt}$), average firm ROA ($Avg\ ROA_{kt}$), average firm book-to-market ratio ($Avg\ BP_{kt}$), average analyst general experience ($Avg\ Exp_{kt}$), and average analyst portfolio size ($Avg\ Port_{kt}$).

We examine the determinants of in-house ESG research provision using the following probit model:

$$\begin{aligned} Prob(ESG\ ResearchB_{kt} = 1) = & \alpha + \beta_1 SI\ Fund_{kt} + \beta_2 ESGP_{kt} + \beta_3 ESGP\ Vol_{kt} + \beta_4 Climate_{kt} + \beta_5 Bkr\ Size_{kt} \\ & + \beta_6 Green\ Bonds_{kt} + \beta_7 Sustain\ Theme_{kt} + \beta_8 Avg\ Size_{kt} + \beta_9 Avg\ ROA_{kt} \\ & + \beta_{10} Avg\ BP_{kt} + \beta_{11} Avg\ Exp_{kt} + \beta_{12} Avg\ Port_{kt} + \varepsilon_{kt} \end{aligned} \quad (1)$$

where k and t denote the brokerage house and year, respectively. The dependent variable is a dummy variable that equals 1 if a broker has in-house ESG research and 0 otherwise. All variable definitions are in [Appendix A](#). Given that in-house ESG research among U.S.-based brokerages first emerged in 2009, our sample period covers 2009–2021.¹⁷ The determinants tests are based on the U.S. sample of 2,100 broker-year observations.

Empirical Results

[Table 2](#) presents the summary statistics of the variables included in the determinants model. On average, 4 percent of U.S. broker-years have in-house ESG research. The percentage is relatively low, as most growth in the U.S. ESG analyst population has only occurred since 2017. [Table 3](#) presents the correlation matrix of variables in the determinants model. In-house ESG research is positively and significantly correlated with all proposed demand-side and supply-side factors. Overall, the correlations are consistent with our expectations. Additionally, the pairwise correlations for the identified factors are below 0.6, suggesting that multicollinearity is unlikely to be a concern for the determinants model.

[Table 4](#) presents the regression results of determinants models. Column (1) reports the baseline determinants model without control variables. Column (2) reports the results with the control variables included, i.e., [Equation \(1\)](#). Considering that brokers with an office in the U.S. but headquarters outside the U.S. could be affected by factors related to their headquarters countries, we control for headquarters country fixed effects in column (3). In column (4),

¹⁵ Although prior studies suggest a positive link between analysts' coverage decisions and investment banking activities ([Bradley et al. 2008](#); [Dechow and You 2012](#); [Degeorge et al. 2007](#)), the U.S. developed a set of regulations, such as Global Analyst Research Settlement and SEC rules, during the period from 2000 to 2003 to address analyst conflicts of interest. These rules prohibit analyst involvement in investment banking business. As the first green bond issuance in our sample is in 2007, we are not suggesting that brokerage houses provide ESG research for underwriting purposes.

¹⁶ Sustainable thematic revenue includes revenues related to human development, resource security, climate action, basic needs, and healthy ecosystems. The revenue data are available from 2020. We classify a firm as sustainable oriented if its most recent percentage of sustainable revenue is larger than zero.

¹⁷ Sample sizes vary depending on test and data availability.

TABLE 2
Summary Statistics for Determinants Models

Variable	Mean	Q1	Median	Q3	Std. Dev.
<i>ESG ResearchB</i>	0.04	0.00	0.00	0.00	0.19
<i>SI Fund</i>	16.12	0.00	22.98	25.45	11.48
<i>ESGP</i>	0.54	0.45	0.54	0.64	0.15
<i>ESGP Vol</i>	0.10	0.06	0.08	0.12	0.06
<i>Climate</i>	0.64	0.00	1.00	1.00	0.48
<i>Bkr Size</i>	23.61	3.00	11.00	24.00	37.84
<i>Green Bonds</i>	0.07	0.00	0.00	0.00	0.26
<i>Sustain Theme</i>	0.64	0.00	1.00	1.00	0.48
<i>Avg Size</i>	7.69	6.96	7.78	8.52	1.28
<i>Avg ROA</i>	0.08	0.02	0.04	0.07	0.13
<i>Avg BP</i>	1.13	0.46	0.62	0.89	2.39
<i>Avg Exp</i>	11.42	7.41	10.49	14.00	6.12
<i>Avg Port</i>	13.59	9.02	12.39	16.38	7.80

This table reports descriptive statistics for variables included in the determinants model of ESG research (Equation (1)) at the broker-year level. The sample consists of 287 unique U.S. brokers and 2,100 broker-year observations from 2009 to 2021. See Appendix A for variable definitions.

TABLE 3
Correlation Matrix for ESG Research and Demand and Supply Factors

	<i>ESG ResearchB</i>	<i>SI Fund</i>	<i>ESGP</i>	<i>ESGP Vol</i>	<i>Climate</i>	<i>Bkr Size</i>	<i>Green Bonds</i>	<i>Sustain Theme</i>
<i>ESG ResearchB</i>	1.000							
<i>SI Fund</i>	0.147***	1.000						
<i>ESGP</i>	0.076***	0.101***	1.000					
<i>ESGP Vol</i>	0.135***	0.030	0.113***	1.000				
<i>Climate</i>	0.116***	0.367***	0.092***	0.078***	1.000			
<i>Bkr Size</i>	0.306***	0.206***	0.178***	-0.001	0.058***	1.000		
<i>Green Bonds</i>	0.272***	0.193***	0.181***	0.115***	0.097***	0.542***	1.000	
<i>Sustain Theme</i>	0.131***	0.157***	0.111***	-0.054**	-0.065***	0.361***	0.162***	1.000

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table reports correlations of variables based on the U.S. sample consisting of 287 unique brokers and 2,100 broker-year observations from 2009 to 2021.

See Appendix A for variable definitions.

we restrict the sample to brokers with headquarters in the U.S. only. As the significance of the demand and supply factors remains consistent across all four regressions, we focus on the result reported in column (2).

On the demand side, the coefficient on sustainable funds (*SI Fund*) is positively significant, consistent with our prediction that buy-side clients' needs for sustainable investments drive the provision of in-house ESG research. Economically, a one standard deviation increase in sustainable fund flow is associated with a 0.29 percent increase in the likelihood of providing ESG research.¹⁸ Given that only 4 percent of sample broker-years provide ESG research, the increase is economically significant. Untabulated results show that this finding is driven by ESG fund flows and, to

¹⁸ We calculate the increase based on regression in column (2). It is calculated as the standard deviation of *SI Fund* (11.48) multiplying the marginal effect at means (0.00025).

TABLE 4
Determinants of In-House ESG Research

	(1)	(2)	(3)	(4)
Variable	DV = ESG ResearchB			
Factors Related to Demand:				
SI Fund	0.0521*** (3.57)	0.0492*** (3.62)	0.0526*** (3.22)	0.0543*** (3.20)
ESGP	−0.7471 (−0.76)	−0.2473 (−0.18)	−0.3459 (−0.26)	−0.1128 (−0.09)
ESGP Vol	3.1031** (2.56)	3.0595* (1.73)	3.3725** (2.06)	3.2858** (1.98)
Climate	0.7499** (2.35)	1.0303*** (2.88)	1.0965*** (3.04)	1.0800*** (2.68)
Factors Related to Supply:				
Bkr Size	0.0081*** (3.11)	0.0079*** (3.20)	0.0076*** (2.66)	0.0090*** (2.87)
Green Bonds	0.1401 (0.50)	0.1480 (0.52)	0.1165 (0.38)	0.1052 (0.27)
Sustain Theme	0.9130** (2.24)	1.2699** (2.26)	1.2658** (2.55)	1.0161** (2.50)
Controls:				
Avg Size		−0.1177 (−0.70)	−0.1065 (−0.64)	−0.0868 (−0.52)
Avg ROA		−0.1114 (−0.10)	−0.2760 (−0.26)	−0.0486 (−0.05)
Avg BP		0.0515 (1.41)	0.0560 (1.44)	0.0423 (1.10)
Avg Exp		−0.0028 (−0.12)	−0.0113 (−0.47)	−0.0037 (−0.16)
Avg Port		0.0034 (0.26)	0.0016 (0.14)	0.0078 (0.74)
Constant	−4.4284*** (−5.76)	−4.2142*** (−3.46)	−4.4976*** (−3.29)	−4.4237*** (−3.66)
Observations	2,100	1,959	1,833	1,782
Headquarter Country FE	N	N	Y	N
Year FE	Y	Y	Y	Y
Pseudo R ²	0.347	0.346	0.363	0.327

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table presents the results of Equation (1). Column (1) presents the baseline model. Column (2) includes additional control variables. Column (3) includes the headquarters country FE. Column (4) restricts the sample to those brokers headquartered in the U.S. The dependent variable is an indicator variable that equals 1 if broker k has in-house ESG research in year t and 0 otherwise. The sample is brokers located in the U.S. from 2009 to 2021. Robust standard errors clustered at the broker level are used to compute the t-statistics in parentheses. See Appendix A for variable definitions.

a lesser extent, impact fund flows. These findings suggest that client demand for ESG research can arise from funds' need to incorporate ESG factors into their investment strategies.

Although the coefficient for ESG performance of firms in the broker's portfolio (*ESGP*) is not significant, ESG performance volatility (*ESGP Vol*) is positively related to in-house ESG research. Economically, a one standard deviation increase in *ESGP Vol* is associated with a 0.09 percent increase in the likelihood of providing ESG research. This suggests that the need for ESG-related risk management influences the decision to provide ESG research, consistent with brokers with higher internal demand being more likely to do so.

Further, the coefficient on *Climate* is positive and significant, providing evidence that local awareness of ESG issues may also increase the demand for in-house ESG research. Economically, brokers in states with finalized state climate adaptation plans have a 0.25 percent higher likelihood of providing ESG research.¹⁹

On the supply side, as expected, the coefficient on brokerage house size (*Bkr Size*) is positive and significant, indicating that large brokerage houses are more likely to provide ESG research (0.15 percent higher likelihood economically). Additionally, the coefficient on *Sustain Theme* is positive and significant, indicating that U.S. brokers covering sustainable thematic industries are more likely to have in-house ESG research. Economically, brokers covering sustainable thematic industries have a 0.31 percent higher likelihood of providing ESG research. However, the coefficient for green bond underwriting (*Green Bonds*) is not significant.

For brokerage-level controls, we do not observe significant coefficients. The Pseudo R^2 is around 34.7 percent (column (1)), indicating that these factors explain a substantial portion of the variation in in-house ESG research. Overall, the results of the determinants models show that the provision of ESG research is related to both demand-side and supply-side factors.²⁰

V. CONSEQUENCES OF IN-HOUSE ESG RESEARCH

To examine the potential impact of in-house ESG research on brokers' equity research, we use equity analysts' earnings forecast accuracy as our main outcome measure. Several studies find that colleagues have positive effects on analyst research. Groysberg and Lee (2008) find that the quality of an analyst's colleagues within her firm affects her performance. Bradley et al. (2019) find that analysts working for high-quality directors of research provide more accurate and informative forecasts. Hugon et al. (2016) find that analysts at brokerage houses with in-house macroeconomists under-react less to macroeconomic news, and their forecast revisions trigger a stronger market reaction. Similarly, in-house ESG research may improve the quality of equity research.

In-House ESG Research and Earnings Forecast Accuracy

Research Design

We first investigate the effect of in-house ESG research on equity analysts' earnings forecast accuracy. Following prior studies (Bradley et al. 2017a; Clement 1999; Malloy 2005), we estimate the following model:

$$PMAFE_{ijt} = \alpha + \beta_1 ESG\ Research_{ijt} + Controls + \varepsilon_{ijt} \quad (2)$$

where the dependent variable is a measure of relative forecasting error developed by Clement (1999), calculated as the proportional mean absolute forecast error ($PMAFE_{ijt}$) of analyst i 's annual earnings forecast for firm j for year t :

$$AFE_{ijt} = Abs(Forecast\ EPS_{ijt} - Actual\ EPS_{ijt}) \quad (3)$$

$$PMAFE_{ijt} = (AFE_{ijt} - MAFE_{jt}) / MAFE_{jt} \quad (4)$$

where AFE_{ijt} is the absolute forecast error for analyst i 's annual earnings forecast of firm j for year t and $MAFE_{jt}$ is the mean absolute forecast error for firm j for year t . As constructed, a smaller $PMAFE$ indicates a smaller relative forecast error and greater forecast accuracy. Our variable of interest is $ESG\ Research_{ijt}$, which equals 1 if the U.S.-based brokerage house that analyst i is affiliated with has in-house ESG research in year t and 0 otherwise.

Following Bradley et al. (2017a), we include a host of analyst-level control variables, including general experience (*Gen Exp*), firm-specific experience (*Firm Exp*), forecast horizon (*Horizon*), the number of stocks and two-digit SIC

¹⁹ Our results are robust when we replace *Climate* with Democratic-leaning states as an alternative overall measure for local ESG awareness. We also note that it is likely that *Climate* is correlated with state policies around social issues and governance as well as specific state initiatives related to ESG (e.g., constraints on ESG investing in Florida and Texas). For this reason, we view *Climate* as an omnibus measure of local ESG awareness.

²⁰ We also examine whether demand or supply factors are stronger at predicting the decision to have ESG research. We use factor analysis and combine the variables into a single demand factor and a single supply factor and re-estimate Equation (1) using the two standardized factors. Untabulated results show that the demand factor has a larger coefficient, although the difference is not statistically significant.

industries followed by analyst i (*Port Size* and *Num SIC2*, respectively), and whether analyst i is affiliated with a top ten percent brokerage house (*Top 10*). We mean-adjust all of the abovementioned variables at the firm-year level to control for firm-year effects. In addition to analyst-level controls, we include firm-level controls, including firm size measured as the natural log of market capitalization (*Size*), book-to-market ratio (*BP*), return-on-asset (*ROA*), loss indicator (*Loss*), the number of analysts following firm j (*Cover*), firm age (*Age*), and firm j 's return over the past 12 months (*Ret*). These firm-level controls are retained in their raw form (i.e., not mean-adjusted) to capture firm-specific characteristics that may influence forecast accuracy.

To tighten the link between in-house ESG research and equity analysts' forecast accuracy, we conduct cross-sectional tests. We examine environmentally sensitive industries, controversial industries, and industries with high SASB disclosure requirements. In these industries, ESG issues are more salient, suggesting that the impact of in-house ESG research on forecast quality will be greater. Following prior studies (Cai, Jo, and Pan 2012; Chatterji and Toffel 2010; García-Meca and Martínez-Ferrero 2021; Hong and Kacperczyk 2009), we define environmentally sensitive industries as those that have negative impacts on the environment, including mining, oil exploration, paper, chemicals, allied products, petroleum refining, metals, and utilities (with SICs of 10, 13, 26, 28, 29, 33, and 49, respectively). Controversial industries include sin industries (i.e., alcohol, tobacco, and gambling) and industries exposed to emerging environmental, social, or ethical issues (e.g., defense-related weapons, nuclear power, oil, cement, and biotech). SASB issues industry standards for 78 industries and identifies material sustainability disclosure topics for each industry, such as air quality, product safety, workforce health, and safety. The number of disclosure topics varies across industries. We define industries with high SASB disclosure requirements if the number of disclosure topics equals or exceeds seven, which corresponds to the top tercile (25 out of 78 industries).²¹ Detailed industry codes are provided in the [Online Appendix](#), Section 3.

Empirical Results

Table 5 reports the regression results for Equation (2), which examine the effects of ESG research on analysts' earnings forecast errors.²² The dependent variable is relative forecast errors (*PMAFE*). Our variable of interest is *ESG Research*. Following prior studies (Bradley et al. 2017a; Clement, Koonce, and Lopez 2007; Jacob, Lys, and Neale 1999), we control for analysts' innate ability by including analyst-firm fixed effects.

Panel A reports the baseline model. Column (1) reports the regression results for the full sample. The coefficient on *ESG Research* is negative but insignificant, indicating that ESG research is not associated with earnings forecast accuracy. Column (2) reports the regression results for environmentally sensitive firms. The coefficient on *ESG Research* is negative and significant (−0.0494), indicating that earnings forecasts issued by analysts at brokers with ESG research are 4.94 percent more accurate than those issued by analysts at other brokers. In contrast, the coefficient on *ESG Research* is not significant in column (3) for non-environmentally sensitive industries, indicating that such outperformance does not exist among these firms. The results are consistent with our prediction that ESG research is more helpful for equity research on firms in environmentally sensitive industries.

Similarly, as expected, the coefficient on *ESG Research* is negative and significant for controversial industries (column (4)) and high SASB disclosure industries (column (6)). Economically, analysts at brokers with ESG research are 6.07 percent and 4.18 percent more accurate for the two industry groups, respectively. These magnitudes are economically meaningful and comparable with those reported in prior studies.²³ We further test the equality of coefficients between ESG-heavy and non-ESG-heavy industries. The Chi-square statistics from Wald tests are significant for all three ESG-heavy industries, indicating that the effects of ESG research on forecast accuracy are significantly stronger for industries with greater exposure to ESG issues.²⁴

To alleviate the concern that the results are driven by analyst-level and firm-level characteristics, in Panel B, we use entropy balancing, which reweights the observations so that the means and variances of analyst and firm controls are nearly identical for analyst-firm-years with and without ESG research (Glendening, Mauldin, and Shaw 2019;

²¹ The results remain similar if the cutoff point is eight or nine.

²² The descriptive statistics for the variables in Equation (2) are reported in the [Online Appendix](#), Section 4.

²³ For example, Bradley et al. (2017a) report a 6.58 percent higher forecast accuracy for analysts with prior industry experience (Table XI, column 2). Bradley et al. (2019) find that analysts with access to industry-aligned directors of research (DORs) issue forecasts that are 3.76 percent more accurate than those without access to such DORs on the same firm.

²⁴ We also estimate Equation (2) using a ranked forecast accuracy measure following Bradley et al. (2017a) and Hong and Kubik (2003). For each firm-year, we rank analysts according to absolute forecast errors. We then convert these ranks into percentile scores ranging from 0 to 100 (see Table IV, p. 322 in Hong and Kubik 2003). To capture persistent forecasting ability and reduce noise, we follow the two studies and take the average of analyst i 's percentile scores over years t , $t-1$, and $t-2$. The results (untabulated) are consistent with our baseline results in Table 5.

TABLE 5

Regressions of Earnings Forecast Accuracy on ESG Research

Panel A: Baseline Model

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ESG Research</i>							
	-0.0003 (-0.03)	-0.0494* (-1.84)	0.0154 (1.02)	-0.0607* (-1.73)	0.0117 (0.82)	-0.0418** (-2.00)	0.0188 (1.14)
<i>Gen Exp</i>	-0.0017*	-0.0037*	-0.0011	0.0001	-0.0021**	0.0007	-0.0027***
<i>Firm Exp</i>	(-1.95)	(-1.91)	(-1.12)	(0.03)	(-2.24)	(0.45)	(-2.60)
	-0.0015	-0.0040	0.0009	-0.0088*	0.0006	-0.0061*	0.0007
<i>Horizon</i>	(-0.69)	(-1.06)	(0.39)	(-1.79)	(0.28)	(-1.66)	(0.27)
	0.0057***	0.0050***	0.0059***	0.0053***	0.0057***	0.0060***	0.0055***
	(66.82)	(27.20)	(63.02)	(28.67)	(61.26)	(40.21)	(55.73)
<i>Port Size</i>	-0.0010	-0.0003	-0.0013	-0.0000	-0.0012	-0.0012	-0.0009
	(-1.36)	(-0.18)	(-1.49)	(-0.02)	(-1.46)	(-0.90)	(-1.09)
<i>Num SIC2</i>	0.0079***	0.0056	0.0087***	-0.0008	0.0091***	0.0050	0.0090***
	(2.84)	(0.94)	(2.83)	(-0.11)	(3.03)	(1.01)	(2.83)
<i>Top 10</i>	-0.0008	0.0148	-0.0068	0.0239	-0.0063	0.0058	-0.0029
	(-0.08)	(0.89)	(-0.66)	(1.14)	(-0.63)	(0.36)	(-0.27)
<i>Cover</i>	-0.0015**	0.0006	-0.0020***	0.0002	-0.0019***	-0.0003	-0.0022***
	(-2.26)	(0.47)	(-2.60)	(0.14)	(-2.66)	(-0.33)	(-2.68)
<i>Size</i>	0.0134***	0.0142*	0.0091*	0.0192**	0.0096**	0.0138**	0.0137**
	(3.08)	(1.90)	(1.78)	(2.32)	(1.96)	(2.00)	(2.54)
<i>BP</i>	-0.0002***	-0.0002***	-0.0019	-0.0002***	-0.0013	-0.0002***	-0.0004
	(-2.64)	(-3.79)	(-1.24)	(-3.92)	(-0.94)	(-2.94)	(-0.22)
<i>ROA</i>	0.0057***	-0.0840**	0.0064***	-0.0703*	0.0063***	-0.0906**	0.0064***
	(6.28)	(-2.04)	(18.96)	(-1.87)	(16.01)	(-2.11)	(23.98)
<i>Loss</i>	-0.0030	0.0029	-0.0075	0.0131	-0.0090	-0.0018	-0.0068
	(-0.48)	(0.26)	(-1.02)	(1.04)	(-1.30)	(-0.19)	(-0.87)
<i>Age</i>	0.0005***	0.0005***	0.0004***	0.0006***	0.0004***	0.0005***	0.0005***
	(3.98)	(2.83)	(2.95)	(3.23)	(3.34)	(2.70)	(3.17)
<i>Ret</i>	-0.0082	-0.0001	-0.0130**	-0.0032	-0.0111*	-0.0059	-0.0111
	(-1.54)	(-0.01)	(-2.00)	(-0.30)	(-1.78)	(-0.72)	(-1.54)
<i>Constant</i>	-0.2264***	-0.2849***	-0.1584***	-0.3179***	-0.1740***	-0.2587***	-0.2086***
	(-4.84)	(-3.60)	(-3.02)	(-4.00)	(-3.45)	(-3.25)	(-3.90)
Test of equal coefficient (Chi-square)		(2) versus (3)	(4) versus (5)			(6) versus (7)	
		4.4194**	3.6461*			5.1841**	
<i>ESG Research</i>							
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	345,906	79,050	266,817	54,828	291,076	106,615	239,281
R ²	0.446	0.412	0.456	0.429	0.449	0.448	0.445

(continued on next page)

TABLE 5 (continued)

Panel B: Entropy Balancing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ESG Research</i>	0.0002 (0.01)	-0.0532** (-2.28)	0.0213 (1.23)	-0.0540* (-1.82)	0.0124 (0.76)	-0.0374* (-1.85)	0.0197 (1.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	345,906	79,050	266,817	54,828	291,076	106,615	239,281
R ²	0.500	0.450	0.514	0.474	0.504	0.490	0.504

Panel C: Dynamic Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ESG Research_{t-2}</i>	-0.0305** (-2.07)	-0.0447 (-1.44)	-0.0273 (-1.59)	-0.0530 (-1.28)	-0.0266 (-1.62)	-0.0148 (-0.56)	-0.0391** (-2.16)
<i>ESG Research_{t-1}</i>	-0.0259 (-1.35)	-0.0356 (-0.94)	-0.0248 (-1.12)	-0.0308 (-0.60)	-0.0251 (-1.22)	-0.0298 (-0.95)	-0.0259 (-1.11)
<i>ESG Research_t</i>	-0.0350* (-1.74)	-0.1174*** (-2.94)	-0.0108 (-0.47)	-0.1500*** (-2.84)	-0.0143 (-0.66)	-0.1207*** (-3.76)	0.0008 (0.03)
<i>ESG Research_{t+1}</i>	-0.0535** (-2.29)	-0.1103** (-2.30)	-0.0396 (-1.49)	-0.1079* (-1.76)	-0.0447* (-1.77)	-0.0818** (-2.16)	-0.0427 (-1.50)
<i>ESG Research_{t+2}</i>	-0.0579** (-2.24)	-0.1386** (-2.44)	-0.0364 (-1.25)	-0.2198*** (-3.17)	-0.0293 (-1.03)	-0.1068** (-2.48)	-0.0402 (-1.30)
<i>ESG Research_{t+3}</i>	-0.0665** (-2.13)	-0.0979 (-1.50)	-0.0590* (-1.67)	-0.1483* (-1.81)	-0.0520 (-1.55)	-0.1091* (-1.95)	-0.0503 (-1.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,678	26,612	88,048	17,107	97,571	34,633	80,038
R ²	0.469	0.422	0.483	0.441	0.474	0.478	0.466

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table presents the regression of analysts' earnings forecast accuracy on ESG research, i.e., Equation (2). For Panels A-C, the dependent variable is the proportional mean absolute forecast error (*PMAFE*) defined as the difference between the absolute forecast error of analyst *i* for firm *j* for year *t* and the mean absolute forecast error for firm *j* for year *t* deflated by the mean absolute forecast error for firm *j* for year *t*. The variable of interest is *ESG Research*, which equals 1 if analyst *i* is affiliated with a U.S. broker with in-house ESG research in year *t*. Analyst and firm controls are included, but not tabulated in Panels B and C. Panel A presents the baseline model results. Panel B presents the results using entropy balancing. Panel C presents the results from a dynamic regression. The Chi-squares are from Wald-test. Robust standard errors double-clustered at the firm and analyst levels are used to compute the t-statistics in parentheses.

See Appendix A for variable definitions.

Hainmueller 2012). An advantage of entropy balancing is that it allows us to retain the full sample. The results are similar to those in Panel A.^{25,26}

Next, we conduct a dynamic analysis and estimate separate coefficients for *ESG Research* from $t-2$ to $t+3$, where t is the year in which ESG research is established. Results in Table 5, Panel C show that the positive effect of ESG research on forecast accuracy in the full sample and ESG-heavy industries becomes evident in the year the ESG research facility is established.

Extent and Quality of ESG Research

Using the subsample of brokers with an ESG research facility, we examine whether the extent and quality of ESG research affect equity analysts' forecast accuracy. We develop three measures to capture the extent and quality. First, we consider the extent of ESG research provision (e.g., whether there is a single ESG analyst or team), the expertise of ESG analysts (e.g., whether ESG analysts have research or finance experience), and the presence of female ESG analysts, because prior studies suggest that female analysts may improve team collaboration, leveraging their interpersonal skills to foster better communication and teamwork (e.g., Bear and Woolley 2011; Hoogendoorn, Oosterbeek, and van Praag 2013).

We re-estimate Equation (2) with each of these measures in place of *ESG Research*. Overall, we find that a more extensive or higher quality ESG research facility is associated with more accurate earnings forecasts in non-ESG-heavy industries. Adding ESG analysts or employing more experienced or female ESG analysts may bring new insights and perspectives, resulting in more useful ESG research for non-ESG-heavy industries where ESG issues may be more varied and subtle than in ESG-heavy industries. A complete discussion of these tests is provided in the Online Appendix, Section 6.²⁷

Information Interpretation Role versus Discovery Role

Although our empirical results indicate that analysts at brokers with in-house ESG research issue more accurate earnings forecasts, it is unclear how in-house ESG research improves forecasts. Similar to equity analysts, in-house ESG analysts can play an information interpretation role and an information discovery role in the ESG integration process. In their interpretation role, in-house ESG analysts assist equity analysts in incorporating existing ESG information, such as corporate sustainability reports, ESG ratings, and media news, into equity valuation. Conversely, in their discovery role, these analysts discover new ESG information and generate novel insights previously unavailable to equity analysts. In this section, we conduct two sets of tests to examine these distinct roles.

Cross-Sectional Tests for Different Firm-Level ESG Characteristics

In the first set of tests, we examine how firm-level ESG-related characteristics moderate the effect of ESG research. First, we examine two characteristics that could complicate the interpretation and integration of ESG information for earnings forecasting. The first is ESG risk (*ESG Risk*), which is measured by the volatility of a firm's ESG rating over the past three years. When ESG performance is unpredictable, forecasting the effects of ESG on earnings becomes more challenging. The second is ESG rating disagreement (*ESG Disagree*), which refers to the standard deviation in ratings among different ESG rating agencies, including Sustainalytics, ASSET4, and KLD. Serafeim and Yoon (2023) find that market reaction to ESG news is weakened by ESG rating disagreement, suggesting that ESG rating

²⁵ We conduct two additional robustness tests. First, we use unadjusted forecast error and analyst characteristics in the regression. Second, we follow Clement (1999) and exclude firm controls when estimating Equation (2). The results for both analyses remain similar and are provided in the Online Appendix, Section 5.

²⁶ To alleviate the concern that the results of consequence models are driven by broker-level factors, we perform two additional tests. First, it is possible that factors identified in the determinants models, such as client demands, are also related to equity analysts' research quality. We include brokerage variables from Table 4 in our models and find consistent results (untabulated). Second, to control unobservable broker-level factors that are associated with both ESG research and research output quality, we control broker fixed effects. The results (untabulated) are similar for earnings forecast accuracy.

²⁷ As an additional analysis, we examine whether the positive impact of ESG research on forecast accuracy depends on the geographic proximity between ESG and equity research analysts within a broker. This analysis builds on the assumption in prior studies that analysts within the same brokerage communicate and share insights through various channels, including research reports, internal meetings, seminars, and training (Birru et al. 2024; Bradley et al. 2024; Hugon et al. 2016). We find that forecast accuracy improves when equity analysts are located in the same city as an ESG analyst or when a larger number of ESG analysts are based in the broker's head-office city, particularly for non-ESG-heavy industries. This evidence suggests that in-person interactions can facilitate the transfer of ESG-related knowledge, especially in non-ESG-heavy industries where relevant ESG issues may be less apparent. In ESG-heavy industries, proximity provides limited incremental improvement in forecast accuracy, suggesting that internal knowledge-sharing platforms and virtual meetings may be sufficient to enable effective cross-location communication where ESG issues are more familiar. A full description of the research design and results is provided in the Online Appendix, Section 7.

disagreement hinders the incorporation of ESG news into stock prices. Therefore, we conjecture that, if ESG analysts play an interpretation role, in-house ESG research would be more valuable when forecasting firms with greater ESG risks and ESG disagreements.

Table 6, Panel A (B) presents the cross-sectional results for the ESG risks (ESG disagreement). The interaction term of ESG research and ESG risk (*ESG Research* $\times$ *ESG Risk*) is negative and significant for the controversial industries and high SASB disclosure industries, indicating that ESG research is particularly useful for firms with greater ESG risk in these industries. Similarly, the coefficients of the interaction term of ESG research and ESG disagreement (*ESG Research* $\times$ *ESG Disagree*) are negative and significant for the controversial industries and high SASB disclosure industries. Collectively, the results provide evidence of ESG analysts' information interpretation role within these two ESG-heavy industries.

Next, we examine the information discovery role of ESG analysts. We use ESG rating coverage (*ESG Cover*) as a proxy for the availability of ESG information from sources other than in-house ESG research. We measure ESG rating coverage as the number of ESG rating agencies (Sustainalytics, ASSET4, and KLD) that cover firm j in year t . The moderating effect of ESG coverage on the relationship between ESG research and earnings forecast accuracy is mixed. When greater ESG rating coverage increases the availability and quality of ESG information, the value of in-house ESG research may be enhanced if ESG analysts primarily help interpret ESG information disclosed by companies. In this case, having access to more ESG information that can be integrated into equity research would make the in-house ESG research more valuable. Conversely, if ESG analysts primarily serve an information discovery role by providing ESG information, the value of in-house ESG research could diminish when abundant ESG information is already available from third-party agencies.

Table 6, Panel C presents the cross-sectional results for the ESG coverage. The coefficient on *ESG Research* is consistently negative and significant across all regressions, indicating that access to in-house ESG research is associated with improved forecast accuracy for firms that are not covered by any of the three ESG rating agencies. In contrast, the coefficient on *ESG Cover* is insignificant in all models. These results suggest that access to third-party ESG ratings data is not associated with greater forecast accuracy for equity analysts without in-house ESG research. This is consistent with the view that ESG integration requires specialized expertise and awareness that may be lacking in the absence of guidance from dedicated ESG analysts. The interaction term (*ESG Research* $\times$ *ESG Cover*) is positive and significant for non-ESG-heavy industries, indicating that the improvement in forecast accuracy is reduced for firms with greater ESG rating coverage. This suggests that the information discovery role of ESG analysts may be more prominent in non-ESG-heavy industries, as the interaction term is either not significant or marginally significant for ESG-heavy industries (columns (2), (4), and (6)).²⁸

In-House ESG Research and Analysts' Incorporation of ESG News

In the second set of tests, we explore how in-house ESG research improves earnings forecasts. We examine a possible channel: whether analysts with access to in-house ESG research better incorporate ESG rating information into forecasts. Prior research shows that analysts under-react or over-react to a wide range of information, including earnings information and nonfinancial information (Abarbanell and Bernard 1992; Raedy, Shane, and Yang 2006; Simpson 2010). Consistently, Cui and Docherty (2020) find that investors over-react to ESG controversies due to cognitive limitations, whereas Glossner (2021) finds that the market under-reacts to ESG incidents. In a parallel context, Hugon et al. (2016) find that, although analysts under-react to negative macroeconomic news, those supported by in-house macroeconomists under-react less. This suggests that the presence of macroeconomists helps analysts better incorporate macroeconomic news into their earnings forecasts. However, the extent to which a similar mechanism exists for ESG information remains unexplored.

Similar to Hugon et al. (2016), we examine whether analysts efficiently incorporate news from ESG ratings and whether in-house ESG research facilitates this incorporation. We estimate the following models:

$$FE_{ijkt} = \alpha + \beta_1 News_{ijt} + \beta_2 LAG_FE_{ijkt} + \text{Controls} + \varepsilon_{ijkt} \quad (5)$$

$$FE_{ijkt} = \alpha + \beta_1 News_{ijt} + \beta_2 ESG\ Research_{ijt} + \beta_3 News_{ijt} * ESG\ Research_{ijt} + \beta_4 LAG_FE_{ijkt} + \text{Controls} + \varepsilon_{ijkt} \quad (6)$$

where FE_{ijkt} is analyst i 's k -quarter-ahead EPS forecast error for firm j in quarter t . Equation (5) examines whether analysts efficiently incorporate ESG news. $News_{ijt}$ refers to ESG news, calculated as the difference between the most recent

²⁸ We also consider the potential effect of equity analyst experience, as ESG analysts may face greater challenges in promoting and implementing ESG integration if equity analysts are very experienced and possess plenty of knowledge about the covering firm. In untabulated analysis, we do not find evidence supporting this notion.

TABLE 6

Cross-Sectional Regressions of Forecast Accuracy on ESG Research

Panel A: ESG Risk

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ESG Research</i>	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ESG Risk</i>	0.0410 (1.18)	-0.0462 (-0.78)	0.0663 (1.61)	0.1359* (1.69)	0.0264 (0.70)	0.0216 (0.47)	0.0491 (1.09)
<i>ESG Research</i> × <i>ESG Risk</i>	0.0149 (0.33)	-0.1202 (-1.52)	0.0632 (1.14)	0.0610 (0.58)	0.0062 (0.12)	-0.0189 (-0.25)	0.0352 (0.63)
Test of equal coefficient (Chi-square)	-0.1463 (-0.86)	-0.2482 (-0.82)	-0.1139 (-0.59)	-1.1560*** (-3.14)	0.0252 (0.14)	-0.6100** (-2.56)	0.0745 (0.37)
<i>ESG Research</i> × <i>ESG Risk</i>		(2) versus (3)		(4) versus (5)		(6) versus (7)	
Observations	92,250	19,764	72,486	11,647	80,603	26,925	65,325
R ²	0.470	0.431	0.480	0.465	0.470	0.480	0.465
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: ESG Disagreement

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ESG Research</i>	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ESG Disagree</i>	0.0402 (1.31)	-0.0335 (-0.66)	0.0594 (1.63)	0.1249* (1.84)	0.0304 (0.91)	0.0144 (0.36)	0.0513 (1.27)
<i>ESG Research</i> × <i>ESG Disagree</i>	-0.0152 (-0.86)	-0.0131 (-0.41)	-0.0141 (-0.67)	0.0805* (1.89)	-0.0306 (-1.55)	-0.0014 (-0.04)	-0.0212 (-0.98)
Test of equal coefficient (Chi-square)	-0.0366 (-0.51)	-0.0662 (-0.53)	-0.0183 (-0.21)	-0.5277*** (-3.37)	0.0439 (0.56)	-0.2313** (-2.50)	0.0630 (0.66)
<i>ESG Research</i> × <i>ESG Disagree</i>		(2) versus (3)		(4) versus (5)		(6) versus (7)	
Observations	129,342	27,227	102,115	16,872	112,470	37,772	91,570
R ²	0.460	0.425	0.469	0.456	0.460	0.468	0.456
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(continued on next page)

TABLE 6 (continued)

Panel C: ESG Rating Coverage

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ESG Research</i>	-0.0760*** (-2.99)	-0.0932** (-2.55)	-0.0649** (-2.06)	-0.1254*** (-3.13)	-0.0610** (-2.06)	-0.0715* (-1.95)	-0.0799** (-2.43)
<i>ESG Cover</i>	-0.0022 (-0.81)	-0.0035 (-0.61)	-0.0019 (-0.62)	-0.0055 (-0.80)	-0.0012 (-0.39)	-0.0042 (-0.91)	-0.0015 (-0.45)
<i>ESG Research</i> × <i>ESG Cover</i>	0.0252 *** (3.45)	0.0156 (1.27)	0.0262 *** (2.92)	0.0238 * (1.68)	0.0238 *** (2.83)	0.0100 (0.89)	0.0325 *** (3.50)
Test of equal coefficient (Chi-square)		(2) versus (3)	(4) versus (5)	(6) versus (7)			
<i>ESG Research</i> × <i>ESG Cover</i>		0.4566					
Observations	345,906	79,050	266,817	54,828	291,076	106,615	239,281
R ²	0.446	0.412	0.456	0.429	0.449	0.448	0.445
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table presents the cross-sectional regression of analysts' earnings forecast accuracy on ESG research. For Panels A–C, the dependent variable is the proportional mean absolute forecast error (*PMAFE*) defined as the difference between the absolute forecast error of analyst *i* for firm *j* for year *t* and the mean absolute forecast error for firm *j* for year *t* deflated by the mean absolute forecast error for firm *j* for year *t*. The variable of interest is the interaction term of ESG research and ESG-related characteristics. Analyst and firm controls are included but not tabulated. Panel A presents the results for ESG risk, measured by ESG performance volatility. Panel B presents the results for ESG disagreement, measured by the standard deviation of ESG ratings received from Sustainalytics, ASSET4, and KLD. Panel C presents the results for ESG rating coverage, measured by the number of agencies that cover the firm. The Chi-squares are from Wald-test. Robust standard errors double-clustered at the firm and analyst levels are used to compute the t-statistics in parentheses. See [Appendix A](#) for variable definitions.

ESG ratings available for quarter t and the previous ESG ratings divided by the previous ESG ratings. We obtain ESG ratings from Sustainalytics from 2009 to 2018.²⁹ We also consider environmental, social, and governance related news separately. As prior studies find evidence of market mispricing of negative ESG news, we examine positive and negative ESG news separately. We obtain quarterly earnings forecasts (one- to four-quarter-ahead) from I/B/E/S, retaining only those issued within 90 days of the availability of ESG news. If analysts over-react (under-react) to ESG news, we should observe a negative (positive) β_1 , as the ESG news predicts analyst forecast errors. Equation (6) examines whether ESG research affects analysts' incorporation of ESG news. If the ESG research alleviates analysts' under- or over-reaction to ESG news, we should observe a β_3 with an opposite sign to that of β_1 .

Table 7 reports the results of analysts' incorporation of negative environmental news (i.e., the newly updated environmental score is lower than the previous one).³⁰ Panel A presents the results of Equation (5). The coefficient on *ENV News* is negative and significant for environmentally sensitive industries and high SASB disclosure industries, indicating that analysts on average over-react to the negative news. However, no over-reaction is observed in other industries, possibly because investors are stricter with firms in ESG-heavy industries and their poor environmental performance is more visible. Panel B reports the results of Equation (6). The coefficient on *ENV News* is significantly negative for all three types of ESG-heavy industries, indicating an over-reaction to negative environmental news. The coefficient on *ESG Research* $\times$ *ENV News* is positive and significant for environmentally sensitive and controversial industries, indicating that ESG research alleviates analysts' over-reaction to negative environmental news in these industries.^{31,32} Taken together, the results suggest that ESG analysts assist equity analysts in both ESG information interpretation and discovery. However, the information interpretation role is more prominent in ESG-heavy industries.

Negative Consequences of ESG Research

Although ESG analysts may assist in information interpretation, we conjecture that, in certain situations, having access to an ESG analyst may not help or even hurt equity analysts' forecasting ability, particularly when the ESG information is difficult to interpret and process. We explore the effect of ESG research on forecast accuracy in the context of social issues, which are difficult to incorporate, as suggested by practitioners in the CFA survey (CFA Institute 2018). We consider whether ESG research is less useful for firms with greater exposure to social issues.

We use the number of material social disclosure topics identified in the SASB industry-specific standards as a proxy for exposure to social issues. We create an indicator, *High Social*, that equals 1 if the number of material disclosure topics is above the median and 0 otherwise. We interact *High Social* with *ESG Research* to examine whether the effect of ESG research depends on a firm's exposure to social issues. Table 8 reports the results. We find that the coefficient on *ESG Research* $\times$ *High Social* is positive and significant for noncontroversial and low SASB disclosure industries, whereas *ESG Research* is not significant in either case.³³ Thus, in these industries, ESG research has no effect on forecast accuracy when exposure to social issues is low, but ESG research is associated with lower forecast accuracy when exposure to social issues is high. Further, we repeat similar analyses using indicators for high material SASB disclosure topics related to the environment and governance, respectively. Unlike the results for social topics, the interactions between these indicators and *ESG Research* are not significant.

In sum, we provide evidence that ESG research is not always useful. There are several reasons why social issues might be more difficult to connect to earnings forecasts than environmental issues. We categorize these challenges into a hierarchy of importance: the conceptual challenge of identifying materiality, the technical challenge of measurement and comparability, and the challenge of analyzing realized outcomes.

The primary impediment to integrating social issues is their multidimensional, diffuse, and context-dependent nature. Unlike the environmental pillar, which increasingly converges on carbon-equivalent metrics and climate risks, the social pillar encompasses a fragmented array of topics, such as health and safety, diversity and inclusion, labor

²⁹ We use Sustainalytics ratings because ASSET4 and MSCI ratings have changed their methodology and applied the changes to historical data. As we aim to examine analysts' reaction to the ESG ratings change, those two ratings are not suitable. We drop the ratings after 2018 because Sustainalytics made a significant change to its rating methodology in 2019. The old ratings are not comparable to the new ratings. As Sustainalytics ratings are issued monthly, we assume that the rating is available at the end of the month.

³⁰ For brevity, the regression results for positive environmental news are reported in the Online Appendix, Section 8. We find no evidence that analysts over- or under-react to positive environmental news (i.e., *ENV News* is insignificant for positive news). We also find no evidence for overall ESG news, social, or governance related news.

³¹ We also try industry and year fixed effects as in Hugon et al. (2016). The coefficient on *ESG Research* $\times$ *ENV News* is positive and significant for all three ESG heavy industries (results untabulated).

³² To be noted, the Sustainalytics ratings are not the only source for ESG news available. Other sources of ESG information include other third-party ESG ratings, company sustainability reports, and news media. To the extent that our measure is incomplete, it will add noise to the measure.

³³ We omit *High Social* from the model due to multicollinearity with the fixed effects.

TABLE 7
Analysts' Incorporation of Negative Environmental News and ESG Research

Panel A: Analysts' Incorporation of Negative Environmental News

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ENV News</i>	-0.0052 (-1.21)	-0.0155* (-1.74)	-0.0000 (-0.01)	-0.0189 (-1.55)	-0.0013 (-0.45)	-0.0168* (-1.82)	0.0001 (0.02)
<i>LAG_FE</i>	0.0758* (1.81)	0.1151** (2.18)	0.0415 (0.68)	0.0695 (0.84)	0.0767 (1.56)	0.1262* (1.68)	0.0203 (0.38)
Constant	0.0099 (0.45)	0.0281 (0.76)	0.0025 (0.12)	0.0543 (1.34)	-0.0101 (-0.51)	0.0173 (0.53)	-0.0182 (-0.87)
Test of equal coefficient (Chi-square)		(2) versus (3)		(4) versus (5)		(6) versus (7)	
<i>ENV News</i>		2.6553		1.9843		3.0451*	
Observations	54,989	16,703	38,279	10,583	44,403	19,847	35,133
R ²	0.512	0.535	0.494	0.568	0.485	0.573	0.430
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: ESG Research and Analysts' Incorporation of Negative Environmental News

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
<i>ENV News</i>	-0.0060 (-1.31)	-0.0189** (-2.10)	0.0007 (0.23)	-0.0219* (-1.83)	-0.0010 (-0.37)	-0.0186** (-2.01)	0.0007 (0.26)
<i>ESG Research</i>	0.0006** (2.06)	0.0016* (1.91)	0.0002 (0.95)	0.0020* (1.87)	0.0003 (1.56)	0.0011* (1.85)	0.0004 (1.44)
<i>ESG Research</i> × <i>ENV News</i>	0.0026 (0.88)	0.0146** (2.51)	-0.0020 (-0.63)	0.0130* (1.70)	-0.0007 (-0.22)	0.0081 (1.55)	-0.0015 (-0.46)
<i>LAG_FE</i>	0.0757* (1.81)	0.1152** (2.19)	0.0415 (0.68)	0.0696 (0.84)	0.0767 (1.56)	0.1262* (1.68)	0.0203 (0.38)
Constant	0.0097 (0.44)	0.0274 (0.74)	0.0023 (0.11)	0.0543 (1.37)	-0.0101 (-0.51)	0.0174 (0.54)	-0.0184 (-0.87)
Test of equal coefficient (Chi-square)		(2) versus (3)		(4) versus (5)		(6) versus (7)	
<i>ENV News</i>		4.2070**		2.8618*		4.0144**	
<i>ESG Research</i> × <i>ENV News</i>		6.2675**		2.7625*		2.4529	
Observations	54,989	16,703	38,279	10,583	44,403	19,847	35,133
R ²	0.512	0.535	0.494	0.568	0.485	0.573	0.430
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* ** *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table presents the regression of analysts' incorporation of negative environmental news, i.e., Equations (5) and (6). The dependent variable is the forecast error calculated as firm j 's actual EPS minus analyst i 's earnings forecast for firm j 's k-quarter-ahead EPS issued in quarter t , scaled by the stock price at the beginning of quarter t . Analyst and firm controls are included, but not tabulated. Panel A presents the results of analysts' incorporation of negative environmental news. The variable of interest is *ENV News*. Panel B presents the results of ESG research and analysts' incorporation of negative environmental news. The Chi-squares are from Wald-test. Firm-year and analyst fixed effects are included. Robust standard errors double-clustered at the firm and analyst levels are used to compute the t-statistics in parentheses.

See Appendix A for variable definitions.

TABLE 8

Exposure to Social Issues

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ESG Research</i>	Full	Env. Sens.	Non-Env. Sens.	Controv.	Non-Controv.	High Disc.	Low Disc.
		−0.0893** (−1.12)	−0.0024 (−0.13)	−0.1501** (−2.05)	−0.0097 (−0.56)	−0.0530 (−1.53)	−0.0072 (−0.39)
<i>ESG Research</i> × <i>High Social</i>	0.0453* (1.68)	0.0684 (1.25)	0.0439 (1.49)	0.1119 (1.37)	0.0555** (1.97)	0.0167 (0.36)	0.0670** (2.09)
Constant	−0.2067*** (−3.86)	−0.2654*** (−2.75)	−0.1473** (−2.51)	−0.2559** (−2.51)	−0.1774*** (−3.14)	−0.1899** (−2.01)	−0.2212*** (−3.67)
Test of equal coefficient (Chi-square)			(2) versus (3) 0.1533	(4) versus (5) 0.4269		(6) versus (7) 0.8025	
<i>ESG Research</i> × <i>High Social</i>							
Coefficient on <i>ESG Research</i> for High Social Disclosure Industries							
<i>ESG Research</i> × <i>High Social</i> + <i>ESG Research</i>	0.0253	−0.0208	0.0415*	−0.0381	0.0458**	−0.0363	0.0597***
Observations	265,708	57,788	207,920	38,853	226,855	79,580	186,122
R ²	0.443	0.404	0.454	0.425	0.446	0.440	0.444
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table presents the cross-sectional regression of analysts' earnings forecast accuracy on *ESG Research*. The dependent variable is the proportional mean absolute forecast error (*PMAFE*), defined as the difference between the absolute forecast error of analyst *i* for firm *j* for year *t* and the mean absolute forecast error for firm *j* for year *t* deflated by the mean absolute forecast error for firm *j* for year *t*. The variable of interest is the interaction term of *ESG Research* and *High Social*, where *High Social* is an indicator equal to 1 if the number of material SASB social disclosures for firm *j*'s industry is above the median and 0 otherwise. Analyst and firm controls are included, but not tabulated. The Chi-squares are from Wald-test. Robust standard errors double-clustered at the firm and analyst levels are used to compute the t-statistics in parentheses.

See [Appendix A](#) for variable definitions.

rights, data privacy, and community relations (OECD 2025). The lack of a dominant dimension increases information processing costs, making it difficult for analysts to assess financial materiality across firms. If an analyst cannot isolate material social issues from the rest, subsequent forecasting modeling could be flawed.

Even when material social issues are identified, social performance remains more difficult to quantify, compare, and interpret than environmental performance. Environmental indicators are increasingly output-based (e.g., emissions, waste reduction, energy usage) and supported by standardized frameworks, such as ISO 14064 and the GHG Protocol. In contrast, about 76 percent of S metrics are qualitative, compared with 67 percent for E, and most quantitative S metrics capture inputs instead of outputs. The lack of standardization prevents analysts from benchmarking social performance across peer firms or incorporating social data into forecasting and valuation models. Consequently, investors identify the social pillar as the most challenging to evaluate due to data scarcity and inconsistency in reporting (BNP Paribas 2021).

The identification and measurement challenges of social issues manifest as increased volatility and regulatory risk at the firm level. Environmental risks, such as carbon pricing or emissions rules, follow known schedules and provide analysts with quantifiable inputs (Duan, Li, and Zhang 2024). In contrast, social risks are idiosyncratic and event-driven. Boycotts, harassment cases, or labor strikes can arise suddenly and affect short-term performance. Their financial impacts depend heavily on public sentiment, media attention, and a firm's crisis-management response (Chen, Ganesan, and Liu 2009; Nuortimo, Harkonen, and Breznik 2026). As a result, similar incidents may lead to different outcomes across firms, making them difficult to model. Moreover, many social issues affect firms indirectly through reputation, employee morale, or customer trust, further complicating the translation of these issues into financial forecasts. Finally, social issues, such as workplace harassment and discrimination, health and safety, consumer protection, and human rights violations, often lead to more regulatory scrutiny, penalties, and lawsuits. The large number and broader scope of social incidents may make it difficult for analysts to track realized incidents and to predict future regulatory risks.

Taken together, these challenges suggest that social information is difficult to identify, measure, interpret, and translate into forecasts and valuations. Prior research on limited attention and information overload suggests that users' processing capacity is constrained, and the complex and excessive information can impair rather than improve judgment (Hirshleifer and Teoh 2003; Chapman et al. 2019). ESG analysts may encourage the incorporation of social-related information into forecasting. However, given these challenges, this incorporation may impose greater cognitive burden, thereby impairing the integration of social information and reducing rather than improving forecast accuracy.

In-House ESG Research and Informativeness of Equity Analysts' Forecast Revisions

If investors recognize the value of in-house ESG research, the market reaction to earnings forecast revisions issued by analysts at brokers with ESG research should be more pronounced. Following Clement and Tse (2003), we estimate the following model:

$$CAR_{ijt} = \alpha + \beta_1 Revision_{ijt} + \beta_2 ESG\ Research_{ijt} \times Revision_{ijt} + \beta_3 ESG\ Research_{ijt} + \beta_4 LagPMAFE_{ijt} + \beta_5 LagPMAFE_{ijt} \times Revision_{ijt} + Controls + \varepsilon_{ijt} \quad (7)$$

The dependent variable is the cumulative abnormal DGTW-adjusted return (CAR_{ijt}) in the three-day window around the earnings forecast announcement $[-1, +1]$ (Daniel, Grinblatt, Titman, and Wermers 1997). $Revision_{ijt}$ is the magnitude of forecast revision measured by the difference between analyst i 's forecast for firm j year t and the previous forecast issued by analyst i for firm j year t scaled by the absolute value of the previous forecast (Ivković and Jegadeesh 2004). If the market reacts more strongly to forecast revisions issued by analysts at brokers with ESG research, β_2 is expected to be positive. We include $LagPMAFE_{ijt}$, which is the $PMAFE$ of analyst i 's forecast for firm j for year $t-1$. In the baseline model, we use unadjusted measures of analyst controls and include firm-year fixed effects to account for variation in forecasting difficulties across firm-years.³⁴

Table 9 reports the regression results of market reaction to earnings forecast revisions (Equation (7)). Column (1) presents the results for the full sample. The coefficient on $ESG\ Research \times Revision$ is not significant, indicating that ESG research is not related to a more pronounced market reaction to forecast revisions. Column (2) reports the results for environmentally sensitive industries. The coefficient on $ESG\ Research \times Revision$ is positive and significant, indicating that earnings forecast revisions issued by analysts from brokers with ESG research evoke a stronger market reaction. Similar to the results of the earnings forecast accuracy model, we find that ESG research is associated with more informative earnings forecast revisions for controversial industries (column (4)) and high SASB disclosure industries (column (6)). In contrast, we

³⁴ Firm controls are omitted because of firm-year fixed effects. Additional untabulated analyses show that the results are similar if we use mean-adjusted measures.

TABLE 9
Regressions of Market Reactions to Earnings Forecast Revisions and ESG Research

Variables	(1) Full	(2) Env. Sens.	(3) Non-Env. Sens.	(4) Controv.	(5) Non-Controv.	(6) High Disc.	(7) Low Disc.
<i>Revision</i>	0.0051*** (4.76)	0.0033* (1.70)	0.0059*** (4.68)	0.0016 (0.77)	0.0062*** (5.09)	0.0040** (2.31)	0.0056*** (4.23)
<i>ESG Research</i>	0.0030 (0.09)	0.1374 (1.45)	-0.0285 (-0.89)	0.2218 (1.62)	-0.0300 (-0.98)	0.0521 (0.69)	-0.0141 (-0.41)
<i>ESG Research × Revision</i>	0.0017 (0.60)	0.0114** (2.31)	-0.0023 (-0.67)	0.0117* (1.83)	-0.0008 (-0.27)	0.0095* (1.95)	-0.0022 (-0.65)
<i>LagPMAFE</i>	-0.0018 (-0.14)	-0.0102 (-0.32)	-0.0009 (-0.07)	-0.0175 (-0.43)	0.0004 (0.03)	0.0036 (0.13)	-0.0050 (-0.34)
<i>LagPMAFE × Revision</i>	0.0006 (0.85)	-0.0008 (-0.58)	0.0013* (1.76)	-0.0017 (-1.03)	0.0014* (1.94)	-0.0005 (-0.36)	0.0012 (1.53)
<i>Gen Exp</i>	-0.0006 (-0.56)	-0.0030 (-0.97)	-0.0000 (-0.02)	-0.0041 (-0.92)	-0.0000 (-0.02)	-0.0002 (-0.10)	-0.0007 (-0.64)
<i>Firm Exp</i>	-0.0017 (-0.72)	0.0064 (1.10)	-0.0040 (-1.57)	0.0161* (1.90)	-0.0044* (-1.83)	0.0041 (0.91)	-0.0043 (-1.55)
<i>Horizon</i>	0.0002 (0.56)	-0.0002 (-0.32)	0.0003 (0.97)	-0.0004 (-0.36)	0.0003 (0.92)	0.0003 (0.44)	0.0001 (0.35)
<i>Port Size</i>	0.0003 (0.18)	0.0003 (0.10)	0.0004 (0.23)	0.0031 (0.68)	-0.0004 (-0.26)	0.0011 (0.35)	-0.0001 (-0.04)
<i>Num SIC2</i>	-0.0069 (-1.17)	-0.0068 (-0.49)	-0.0070 (-1.10)	-0.0220 (-1.01)	-0.0045 (-0.76)	-0.0133 (-1.22)	-0.0041 (-0.60)
<i>Top 10</i>	-0.0119 (-0.54)	-0.0993 (-1.50)	0.0125 (0.60)	-0.1632* (-1.88)	0.0135 (0.66)	-0.0775 (-1.54)	0.0149 (0.67)
Constant	-0.0108 (-0.28)	0.0135 (0.14)	-0.0213 (-0.53)	-0.0520 (-0.39)	-0.0085 (-0.22)	-0.0227 (-0.28)	-0.0081 (-0.19)
Test of equal coefficient (Chi-square)		(2) versus (3)		(4) versus (5)		(6) versus (7)	
<i>ESG Research × Revision</i>		5.2276**		3.1312*		3.9087**	
Observations	249,868	54,123	195,745	35,177	214,691	74,558	175,310
R ²	0.362	0.282	0.404	0.292	0.390	0.332	0.383
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table presents the regression analysis of market reactions to earnings forecast revisions on ESG research, i.e., Equation (7). The dependent variable is the cumulative abnormal return over the three-trading-day window around the announcement date of forecast revision (i.e., $CAR[-1,+1]$). The variable of interest is the interaction term of revision and ESG research ($ESG\ Research \times Revision$). The Chi-squares are from Wald-test. Firm-year fixed effects are included. Robust standard errors double-clustered at the firm and analyst levels are used to compute t-statistics in parentheses. All coefficients are multiplied by 100.

See Appendix A for variable definitions.

do not observe similar outperformance in nonsensitive industries, noncontroversial industries, and low SASB disclosure industries (columns (3), (5), and (7)). The Chi-square is significant for all three types of ESG-heavy industries, indicating that the effects of ESG research on forecast revision informativeness are significantly stronger for ESG-heavy industries.

Other Outputs of Equity Analysts

To shed light on the different ways ESG analysts may help equity analysts, we consider alternative outputs beyond earnings forecasts. For brevity, we report the results for these tests only for environmentally sensitive industries in Table 10, whereas the full results are reported in the Online Appendix. First, we consider the impact of in-house ESG research on analysts' target price forecast accuracy. As reported in Table 10, column (1) and in Table OA.7 of the Online Appendix, ESG research is positively correlated with target price forecast accuracy measured by the price-

TABLE 10
Regression of Other Analyst Outputs and ESG Research

	(1)	(2)	(3)	(4)	(5)
	Target Price Accuracy		Market Reaction to Recommendations		Analyst Reports
	DV = Target Price Absolute Error	DV = Target Price Met	DV = CAR[−1,+1] to Up. Recom. Revision	DV = CAR[−1,+1] to Down. Recom. Revision	DV = ESG Headlines in Analyst Reports
Variable	Env. Sens.				Env. Sens.
<i>ESG Research</i>	−0.0133** (−2.18)	0.0361*** (4.42)	0.0331* (1.84)	−0.0051 (−0.59)	0.2848** (2.26)
<i>AFE</i>	0.4193*** (2.94)	0.1506*** (4.08)	0.0489 (1.38)	0.0034 (0.14)	0.0028 (0.57)
<i>Gen Exp</i>	0.0084** (2.48)	−0.0007 (−0.17)	0.0259** (2.45)	−0.0124** (−2.54)	−0.0094 (−0.17)
<i>Firm Exp</i>	0.0003 (0.90)	−0.0017*** (−3.00)	0.0007 (0.90)	−0.0006 (−1.33)	0.1094 (0.66)
<i>Port Size</i>	−0.0003 (−0.60)	−0.0008** (−1.98)	−0.0012 (−1.27)	−0.0009** (−2.32)	−0.0010 (−0.06)
<i>Num SIC2</i>	0.0009 (0.53)	0.0031 (1.37)	−0.0026 (−0.49)	0.0046** (2.19)	0.0021 (1.10)
<i>Top 10</i>	0.0079 (1.48)	−0.0064 (−0.94)	0.0126 (1.05)	0.0031 (0.42)	0.0424 (0.48)
					<i>Sustain Theme</i> −0.0189 (−1.02)
					<i>Avg Size</i> 0.0317 (1.22)
					<i>Avg ROA</i> −0.0715 (−0.70)
					<i>Avg BP</i> −0.0030 (−0.60)
					<i>Avg Exp</i> −0.0008 (−0.31)
					<i>Avg Port</i> −0.0023** (−2.30)
Constant	0.3433*** (8.16)	0.5770*** (10.57)	−0.2936** (−2.48)	0.1510** (2.54)	−0.2366 (−1.07)
Obs.	165,597	179,365	2,009	2,217	1,279
R ²	0.654	0.396	0.534	0.531	0.591
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes

*, **, *** Indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

This table presents the regression results of other analysts' outputs on ESG research for environmentally sensitive industries. Full results for the entire sample are reported in the [Online Appendix](#). The dependent variable in column (1) is the target price forecast error (*TPERR*), defined as the absolute difference between the forecasted target price and the actual price on the last day of the 12-month forecast period scaled by the actual price on the forecasted date, column (2) is the target price met indicator (*TPMETIN*), defined as a dummy variable that equals 1 if the target price is met during the 12-month forecast period and 0 otherwise, column (3) (column (4)) is the cumulative abnormal return over the three-trading-day window around the announcement date of upward (downward) recommendation revision (i.e., *CAR*[−1,+1]), and column (5) is the number of equity reports with an ESG-related headline for each broker-year. The variable of interest is *ESG Research*, which equals 1 if analyst *i* is affiliated with a broker with ESG research in year *t*.

See [Appendix A](#) for variable definitions.

deflated absolute target price forecast error for all three ESG-heavy industries. Moreover, target prices issued by analysts with access to ESG research are more likely to be achieved during the forecast period in ESG-heavy industries, shown in Table 10, column (2) and in the Online Appendix. However, we do not observe similar improvements in non-ESG-heavy industries.

Second, we test whether investors react more strongly to analyst recommendations issued by brokers with ESG research. We regress $CAR[-1,1]$ around recommendation revisions on ESG research. We split recommendations into upward and downward revisions. As reported in Table 10, columns (3) and (4) and in Table OA.8 of the Online Appendix, we find stronger reactions to upward recommendation revisions, but not downward revisions, issued by analysts at brokers with in-house ESG research, particularly in environmentally sensitive and high SASB disclosure industries. The asymmetric findings are consistent with prior research (Fang and Yasuda 2014; Stickel 1992), which finds similar asymmetry in star analysts' stock recommendations and earnings forecast revisions. Mikhail, Walther and Willis (1997) suggest that analysts delay downward revisions, and as such, the market may incorporate negative news before analysts do.

Third, as detailed in the Online Appendix, Section 11, we provide preliminary evidence on the number of ESG-related words and ESG-related headlines in equity analysts' reports.³⁵ We find that reports issued by equity analysts with access to in-house ESG research contain significantly more ESG-related words and that the number of ESG-related words increases significantly following the initiation of a dedicated ESG research facility. Similarly, reports issued by equity analysts with access to in-house ESG research have more ESG-related headlines, as shown in Table 10, column (5) for environmentally sensitive industries.

VI. CONCLUSION

We examine the determinants and consequences of brokerage in-house ESG research. In terms of the determinants, we identify various factors related to the broker's provision of ESG research, including brokerage house size, buy-side client demand, and ESG risk management. In terms of the consequences, we examine the effects of ESG research on equity research and find that ESG research is associated with higher quality of equity research in ESG-heavy industries, including forecast accuracy, forecast revision informativeness, target price accuracy, and upward recommendation informativeness. Overall, our study contributes to the literature by shedding light on in-house ESG research at a time when ESG issues are becoming more visible and gaining increased attention among investors and the public.

As our empirical analysis focuses on brokerage houses in the U.S., future research can investigate the cross-country heterogeneity in how ESG analysts support equity analysts. Additionally, our early exploratory evidence shows that access to ESG analysts may inadvertently reduce forecast accuracy for firms with high exposure to social issues. Although we discuss various challenges that may collectively impair the integration process, future research could more formally examine the mechanisms. For example, future studies could utilize textual analysis and investigate whether the decline in forecast accuracy is due to the breadth of social topics (i.e., multidimensionality) or the qualitative nature of social disclosures (i.e., lack of comparability). Also, our preliminary evidence on the human capital of ESG analysts invites further investigation into whether specialized professional backgrounds, such as legal, regulatory, or human resources expertise, can mitigate social information processing costs and improve analyst equity research.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

We acknowledge the use of Grammarly and ChatGPT to proofread the manuscript, refine the phrasing, check for grammatical errors, and ensure the readability of this manuscript. All research ideas, conceptual arguments, empirical analyses, interpretations, and conclusions are solely the original work of the authors.

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³⁵ For the ESG-related words test, we collect analyst reports for 12 firms, including the six largest ESG-heavy firms and the six largest non-ESG-heavy firms, based on a composite rank of market value, sales revenue, and analyst coverage. We then identify brokers covering these firms in Investext via Mergent Online in 2017 and 2021 and randomly select one analyst report from each broker, resulting in a sample of 235 analyst reports. Given the relatively small and selected sample, the result should be interpreted with caution.

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APPENDIX A

Variable Definitions

Variable	Definition
Determinants of Research Services	
<i>ESG Research</i>	Indicator variable that equals 1 if broker <i>k</i> has ESG research in year <i>t</i> and 0 otherwise.
<i>SI Fund</i>	Natural log of 1 plus the sum of the size of all sustainable investment funds in the city where broker <i>k</i> 's office is located in year <i>t</i> .
<i>Climate</i>	Indicator variable that equals 1 if broker <i>k</i> 's office is located in a state that has finalized state-level climate change adaptation plan(s) in year <i>t</i> and 0 otherwise.
<i>Green Bonds</i>	Indicator variable that equals 1 if broker <i>k</i> is an underwriter of green bonds in year <i>t</i> and 0 otherwise.
<i>Sustain Theme</i>	Indicator variable that equals 1 if broker <i>k</i> covers firms with sustainable thematic revenues (human development, resource security, climate action, basic needs, and healthy ecosystems) in year <i>t</i> and 0 otherwise.
<i>Bkr Size</i>	Number of analysts issuing annual earnings forecasts for U.S. firms from broker <i>k</i> in year <i>t</i> .
<i>Avg Size</i>	Mean of size for all firms covered by all analysts in broker <i>k</i> in year <i>t</i> . Firm size is the natural log of market capitalization of the covered firm (in \$ millions) by the end of the month before the earnings forecast is issued by analyst <i>i</i> .
<i>Avg ROA</i>	Mean of ROA for all firms covered by all analysts in broker <i>k</i> in year <i>t</i> . ROA is return on assets ratio.
<i>AVG BP</i>	Mean of BP for all firms covered by all analysts in broker <i>k</i> in year <i>t</i> . BP is book-to-market ratio, calculated as book value of equity of firm <i>j</i> in the fiscal year prior to the earnings forecast divided by its current market value of equity at the end of the month when the earnings forecast is issued by analyst <i>i</i> .
<i>Avg Exp</i>	Mean of general experience for all analysts affiliated with broker <i>k</i> in year <i>t</i> . General experience is defined as the number of years since analyst <i>i</i> issued the first annual earnings forecast in I/B/E/S.
<i>Avg Port</i>	Mean of portfolio size for all analysts affiliated with broker <i>k</i> in year <i>t</i> . Portfolio size is the number of firms followed by analyst <i>i</i> in year <i>t</i> .
<i>ESGP</i>	Value-weighted ESG performance of all firms covered by broker <i>k</i> in year <i>t</i> . ESG performance is calculated as the average percentile ranks of Sustainalytics, ASSET4, and KLD ESG ratings for firm <i>j</i> in year <i>t</i> . KLD ESG ratings is calculated as the number of strengths minus the number of concerns.
<i>ESGP Vol</i>	Value-weighted ESG performance volatility of all firms covered by broker <i>k</i> in year <i>t</i> . ESG performance volatility is calculated as the standard deviation of ESGP for firm <i>j</i> in years <i>t</i> , <i>t</i> -1, and <i>t</i> -2.
Earnings Forecast Accuracy Models and Forecast Revision Informativeness Models	
<i>PMAFE</i>	Proportional mean absolute forecast error calculated as the difference between the absolute forecast error (<i>AFE</i>) for analyst <i>i</i> 's annual earnings forecast of firm <i>j</i> for year <i>t</i> and the mean absolute forecast error (<i>MAFE</i>) for firm <i>j</i> in year <i>t</i> scaled by <i>MAFE</i> for firm <i>j</i> in year <i>t</i> .
<i>CAR</i>	DGTW adjusted return, i.e., cumulative abnormal returns calculated following Daniel et al. (1997) over the three-trading-day window [-1,+1] around analyst forecast revision.
<i>ESG Research</i>	Indicator variable that equals 1 if the broker analyst <i>i</i> affiliated with has ESG research located in the U.S. in year <i>t</i> and 0 otherwise.
<i>Gen Exp</i>	The number of years since analyst <i>i</i> issued the first annual earnings forecast in I/B/E/S.
<i>Firm Exp</i>	The number of years since analyst <i>i</i> issued the first annual earnings forecast for firm <i>j</i> in I/B/E/S.
<i>Horizon</i>	The number of days from the forecast date to 30 days before the fiscal period end.
<i>Port Size</i>	Portfolio size is the number of firms followed by analyst <i>i</i> at year <i>t</i> when the earnings forecast is issued.
<i>Num SIC2</i>	Number of SIC industries followed by analyst <i>i</i> at year <i>t</i> when earnings forecast is issued.
<i>Top 10</i>	Indicator variable with the value of 1 if analyst <i>i</i> works at a top decile broker (in terms of the number of analysts) at year <i>t</i> when the earnings forecast is issued and 0 otherwise.
<i>Cover</i>	Number of analysts following firm <i>j</i> at year <i>t</i> when the earnings forecast is issued.
<i>Size</i>	The natural log of market capitalization (ME) of the covered firm (in \$ millions) by the end of the month before the earnings forecast is issued by analyst <i>i</i> .

(continued on next page)

APPENDIX A (continued)

<i>BP</i>	Book-to-market ratio, calculated as the book value of equity of firm <i>j</i> in the fiscal year before the issuance of the earnings forecast, divided by its current market value of equity at the end of the month when the earnings forecast is issued by analyst <i>i</i> .
<i>ROA</i>	Return on asset ratio of firm <i>j</i> in the most recent fiscal quarter before the earnings forecast is issued by analyst <i>i</i> .
<i>Loss</i>	Indicator variable with the value of 1 if firm <i>j</i> reports loss in the most recent fiscal quarter before the earnings forecast is issued by analyst <i>i</i> and 0 otherwise.
<i>Age</i>	Firm age, measured in months, for firm <i>j</i> in the month when analyst <i>i</i> issues the earnings forecast.
<i>Ret</i>	CRSP value-weighted, index-adjusted, buy-and-hold abnormal return (BHARs) of firm <i>j</i> over the 12 months prior to the day when the earnings forecast is issued by analyst <i>i</i> .
<i>Revision</i>	Forecast revision following Ivković and Jegadeesh (2004). Revision is defined as the difference between analyst <i>i</i> 's forecast for firm <i>j</i> for year <i>t</i> at time <i>k</i> and the previous forecast at time <i>k</i> −1 scaled by the absolute value of the forecast at time <i>k</i> −1. The denominator is set to 0.01 if lower. Values are multiplied by 100 and are truncated between −50 percent and 50 percent.
<i>LagPMAFE</i>	Lagged <i>PMAFE</i> is defined as <i>PMAFE</i> of the most recent earnings forecast issued by analyst <i>i</i> for firm <i>j</i> for year <i>t</i> −1.
Cross-Sectional Tests of Forecast Accuracy	
<i>ESG Risk</i>	ESG performance volatility for firm <i>j</i> in year <i>t</i> , calculated as the standard deviation of ESGP for firm <i>j</i> in years <i>t</i> , <i>t</i> −1, and <i>t</i> −2. ESG performance is calculated as the average percentile ranks of Sustainalytics, ASSET4, and KLD ESG ratings for firm <i>j</i> in year <i>t</i> .
<i>ESG Disagree</i>	ESG disagreement, calculated as the standard deviation of the average percentile ranks of Sustainalytics, ASSET4, and KLD ESG ratings for firm <i>j</i> in year <i>t</i> .
<i>ESG Cover</i>	The number of agencies (Sustainalytics, ASSET4, and KLD) providing ESG ratings for firm <i>j</i> in year <i>t</i> . It ranges from 0 to 3.
Analysts' Reaction to ESG News	
<i>FE</i>	Forecast error calculated as firm <i>j</i> 's actual EPS minus analyst <i>i</i> 's earnings forecast for firm <i>j</i> 's <i>k</i> -quarter-ahead EPS issued in quarter <i>t</i> , scaled by the stock price at the beginning of quarter <i>t</i> .
<i>ENV News</i>	Environmental news, calculated as the difference between the most recent Sustainalytics environmental ratings available for quarter <i>t</i> and the previous environmental ratings divided by the previous environmental ratings.
<i>LAG_FE</i>	The lagged forecast error calculated as firm <i>j</i> 's actual EPS minus analyst <i>i</i> 's earnings forecast for firm <i>j</i> 's <i>k</i> -quarter-ahead EPS issued in quarter <i>t</i> −1, scaled by the stock price at the beginning of quarter <i>t</i> −1.