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ESG expertise and analysts' roles in capital markets

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ABSTRACT

Financial analysts are key information intermediaries and external monitors in capital markets, producing earnings forecasts and revisions that shape investors' expectations and asset prices. This study examines whether analysts differ in their ability to process an increasingly important but complex information dimension, environmental, social, and governance (ESG) information, and how such differences affect forecast performance, market reactions, and monitoring outcomes. We use the extent of prior exposure to ESG information as a proxy for analyst ESG expertise and examine its influence on their roles in the capital market. For the information intermediary role, we find that analysts with more industry-specific ESG expertise issue more accurate forecasts and their upward forecast revisions evoke stronger market reactions, indicating that ESG expertise is positively related to analysts' forecast quality. In terms of the external monitor role, we find that more coverage by analysts with greater industry-specific ESG expertise (ESG expert analysts) is positively associated with firms' ESG performance. Additional analysis shows that ESG expert analyst coverage increases after a firm receives its initial third-party ESG rating, suggesting that ESG expert analysts do consider ESG-related firm information when making coverage decisions.

1. Introduction

Financial analysts play a central role in capital markets by producing earnings forecasts and forecast revisions that shape investors' expectations and move asset prices. A large literature examines how analysts' expertise and specialization affect forecast accuracy, revision, and the market's reaction to analyst information (Bradley, Gokkaya, & Liu, 2017; Clement, Koonce, & Lopez, 2007; Mikhail, Walther, & Willis, 1997). This line of research shows that industry specialization, firm-specific experience, collaboration networks, and geographic proximity improve analysts' information processing and the informativeness of their forecasts, highlighting the importance of specialized knowledge in financial analysis (Bae, Stulz, & Tan, 2008; Cao & Liang, 2024; Hilary & Shen, 2013; Malloy, 2005).

An increasingly important but understudied dimension of analyst expertise relates to environmental, social, and governance (ESG) information.[1] ESG issues have become value-relevant as they affect firms' risk exposures, financial performance, access to external finance, and long-run growth opportunities (Cheng, Ioannou, & Serafeim, 2014; Khan, Serafeim, & Yoon, 2016; Lins et al., 2017; Sassen, Hinze, & Hardeck, 2016). At the same time, integrating ESG information into financial forecasts is challenging because ESG data are noisy, heterogeneous, and difficult to map into traditional valuation models (Amel-Zadeh & Serafeim, 2018). As a result, analysts likely differ substantially in their ability to process ESG-related information, creating cross-sectional variation in forecast performance and market reactions.

Consistent with this view, a survey conducted by the Chartered Financial Analyst (CFA) Institute in 2018 shows that over 40% of portfolio managers and financial analysts consider that a "lack of comparable and historical data" and a "limited understanding of ESG issues and ESG integration" among investors are important barriers that have limited the full utilization of ESG information in US capital markets (CFA, 2018). Moreover, in a corresponding workshop, practitioners mentioned that "ESG integration requires a different skill than the number crunching many analysts are used to." The evidence suggests that processing ESG-related information poses substantial challenges even for sophisticated market participants. However, most prior academic studies focus on the effect of firm-level ESG information on

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[1] Prior research uses ESG and corporate social responsibility (CSR) interchangeably. In this study, we treat environmental, social, and governance information and CSR information as being equivalent.

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aggregate analyst forecast quality, thus treating analysts as a homogeneous group and ignoring that the ability to utilize ESG information can vary between analysts. One exception is Kopita and Petrou (2024) (KP hereafter), who find that analysts' ESG experience is positively related to their stock recommendation informativeness. Our findings align with KP in showing that ESG expertise improves analysts' research output quality, particularly earnings forecasts, consistent with their role as information intermediaries. In contrast to Kopita and Petrou (2024), our work further examines the impacts of ESG expertise on analysts' monitoring roles and their coverage decisions. We elaborate on these distinctions later in this section. We consider whether analysts who have more exposure to ESG information perform differently from analysts with less exposure, both as information intermediaries and external monitors.

Following prior studies on analysts' task-specific experience (Clement et al., 2007; Hilary & Shen, 2013), we measure an analyst's raw ESG expertise based on their exposure to ESG-rated stocks, measured as the cumulative number of such stocks in their portfolio over the past five years. We use ESG ratings as they provide a consistent, comparable measure of ESG performance, and it is more likely that analysts will be exposed to and incorporate the ESG information in their assessments. Given that analysts often cover firms within one or several related industries, and prior studies have documented analysts' industry-specific knowledge (Bradley et al., 2017; Jacob, Lys, & Neale, 1999; Kadan, Madureira, Wang, & Zach, 2012), we separate the raw ESG expertise measure into industry-specific ESG expertise and non-industry ESG expertise, which are gained from covering firms across other industries. Considering that analysts who cover more firms and have longer experience are more likely to encounter firms with ESG ratings, we apply an orthogonalization approach to adjust for general coverage patterns and refine our measures of ESG expertise.[2]

Analysts are typically viewed as information intermediaries as they collect and process information about firms and industries and disseminate their investment opinions in the form of published research reports and private communications. Analysts with high research quality facilitate information flows between firms and capital markets and improve firms' information environment. To explore the effect of industry ESG expertise on analysts' information intermediary role, we examine the relation between industry ESG expertise and analysts' forecast accuracy. Using analysts' annual earnings forecasts from 2010 to 2018, we find that industry ESG expertise is associated with higher forecast accuracy. Furthermore, the positive relation between industry ESG expertise and forecast accuracy is stronger for firms with ESG ratings, consistent with these ratings being a viable source of information for analysts with industry ESG expertise. In contrast, non-industry ESG expertise is *not* associated with forecast accuracy.

Next, we examine the market reactions to analysts' forecast revisions. We find that the market reacts more strongly to upward revisions from analysts with more industry ESG expertise. However, market reactions to downward revisions are not significantly related to industry ESG expertise. This is similar to Stickel (1992), Stickel (1995), and Mikhail et al. (1997), who find different effects of firm-specific experience on analysts' upward and downward recommendation revisions informativeness. Overall, the evidence suggests that industry ESG expertise can enhance analysts' forecasting performance.

In addition, analysts have a monitoring role (Jensen & Meckling, 1976). Prior studies examine the relation between analyst coverage and various governance issues, such as earnings management (Irani & Oesch, 2016; Yu, 2008), CEO compensation, cash holding, and value-destroying acquisitions (Chen, Harford, & Lin, 2015). However, the evidence for the relation between analyst coverage and ESG performance is mixed (Adhikari, 2016; Bradley et al., 2022; Qian, Lu, & Yu, 2019). We examine the influence of coverage by analysts with greater than median industry ESG expertise (ESG expert coverage, hereafter). We find ESG expert coverage is related to improved ESG performance in the following year, while the relation between non-ESG expert coverage and ESG performance is not significant. This suggests that only ESG expert analysts play an effective monitoring role in improving firms' ESG performance.

The above evidence indicates that analysts with industry ESG expertise serve both an information intermediary role and a monitoring role. We find further evidence that ESG expert analysts take firms' ESG rating availability into account when making coverage decisions. Using the coverage initiation by a third-party ESG rating provider as an exogenous shock, we find that firms with ESG rating initiations by Sustainalytics, ASSET4, or Bloomberg experience a significantly higher increase in ESG expert analyst coverage than propensity-score matched control firms. The evidence implies that ESG expert analysts recognize their advantage in processing and interpreting ESG information.

Our collective findings contribute to the literature on financial analysts and information specialization by identifying a new dimension of analyst expertise, industry-specific ESG expertise, and examining its effects on forecast performance, revision informativeness, and analyst behavior. Complementing prior studies on analyst expertise (Clement et al., 2007; Hilary & Shen, 2013), we show that ESG expertise is an important form of specialized non-financial knowledge that shapes analysts' information processing and forecast performance. Consistent with practitioner evidence from the CFA Institute documenting substantial heterogeneity in ESG integration skills, we find that only industry-specific ESG expertise improves forecast accuracy and revision informativeness and leads to stronger market reactions to forecast revisions, whereas non-industry ESG expertise has little or even negative effects. These results provide new evidence that industry-specific ESG expertise enhances analysts' forecasting performance and the informativeness of their research outputs.

We further extend the literature on analyst coverage and monitoring by showing that ESG expertise also shapes analysts' coverage decisions and firm outcomes. Building on studies of analyst monitoring (Chen et al., 2015; Irani & Oesch, 2016; Kim et al., 2019) and analyst heterogeneity in monitoring (Bradley et al., 2017; Yu, 2008), we document that greater coverage by analysts with industry-specific ESG expertise is positively associated with subsequent improvements in firms' ESG performance and that ESG-expert analysts are more likely to initiate coverage following a firm's initial third-party ESG rating. In contrast to Adhikari (2016) and Qian et al. (2019), who examine total analyst coverage and find a negative relation with ESG performance, our more granular analysis highlights the importance of analyst expertise in understanding how coverage affects firms' ESG practices. Our findings also complement Ioannou & Serafeim (2015), who show that analysts with longer general experience adopt more favorable views of ESG earlier, by demonstrating that analysts with ESG expertise exhibit systematically different behavior and outcomes.

Another contribution of our study is the conceptual distinction between industry-specific and non-industry ESG expertise. While concurrent work by KP examines whether analysts' general ESG experience improves research outputs, it treats ESG expertise as homogeneous. We show that this aggregation masks important heterogeneity: because ESG issues, materiality, and financial relevance vary widely across industries (Khan et al., 2016; SASB), only industry-specific ESG expertise improves forecast accuracy, revision informativeness, and firm outcomes, whereas non-industry ESG expertise can be neutral or even detrimental. These findings demonstrate that ESG expertise is not a homogeneous construct and that the industry relevance of ESG exposure critically shapes analysts' performance.

Finally, our study differs from KP along several important dimensions. First, we introduce a task-specific measure of ESG expertise based on the cumulative number of ESG-rated firms in an analyst's portfolio over the past five years (Clement et al., 2007), capturing both the depth and breadth of ESG exposure and isolating ESG expertise from

[2] The detailed methodology is described in section 2.2.

general coverage patterns. Second, while KP focus primarily on analysts' information intermediary role through recommendation informativeness, we examine forecast accuracy, revision informativeness, coverage behavior, and firm outcomes, providing a more comprehensive view of how ESG expertise shapes analysts' information production and acquisition. Third, we show that our results are robust across ESG rating systems by using Sustainalytics ratings in the main analysis and LESG ASSET4 ratings as robustness checks, broadening the generalizability of our findings.

The remainder of the paper proceeds as follows. Section 2 covers the background, hypotheses, research design, and empirical results on ESG expertise and the intermediary information role. Section 3 focuses on ESG expert analysts' monitoring role, Section 4 examines the impact of ESG rating initiations on the coverage decisions of ESG expert analysts, and Section 5 concludes.

2. Part I: ESG expertise and information intermediary role

2.1. Background and hypotheses

As information intermediaries, analysts gather information about firms and industries and disseminate investment opinions in the form of research outputs and direct communications with clients. As analysts' research outputs such as forecasts and recommendations are observable, a vast literature studies analysts' expertise by examining their forecasting performance. The most frequently examined attribute is forecast accuracy. Evidence shows that sell-side analysts are not equally accurate. Extant studies investigate and find various factors influencing forecast accuracy. These factors can be classified into two types: (1) relevant expertise such as experience and knowledge, and (2) resources, time, and effort available (e.g., brokerage house size, analyst portfolio size, portfolio geographic proximity) (Clement, 1999; Jacob et al., 1999; Jennings, Lee, & Matsumoto, 2017).

The research on relevant expertise is most pertinent for this study. Early research finds that the years of analysts' experience are related to improved forecasting accuracy. For example, Mikhail et al. (1997) find that analysts following a firm for a longer time issue more accurate forecasts, consistent with the "learning-by-doing" model (i.e., analysts' forecasting ability improves with repetition). Clement et al. (2007) define task-specific experience as the "analyst's experience in forecasting around a particular kind of situation or event". They provide evidence of the importance of task-specific experience by showing that analysts who have experience analyzing firms that have restructured make more accurate forecasts for firms that restructure in the future. In a similar vein, Hilary and Shen (2013) find that analysts who observe more management forecasts issue more accurate forecasts. Bradley et al. (2017) find that analysts make more accurate forecasts if they have worked in a related industry before they became analysts.

Besides forecast accuracy, another broadly examined attribute is the information content of research outputs. Prior research generally suggests that analysts' research outputs are informative as measured by market reaction to these outputs (Bradshaw, Ertimur, & O'Brien, 2017). Similar to forecast accuracy, prior studies investigate the cross-sectional variation in the informativeness of forecast revisions. For example, the informativeness of these revisions can vary with forecast accuracy (C. W. Park & Stice, 2000), investor sophistication (Bonner, Walther, & Young, 2003), forecast timeliness (Clement & Tse, 2003), potential brokerage profits and processing costs (Frankel, Kothari, & Weber, 2006), and broker-host conference connections (Green, Jame, Markov, & Subasi, 2014).

Despite the evidence that analysts' forecast accuracy is positively associated with the information content of forecast revisions and recommendations (Ertimur, Sunder, & Sunder, 2007; Loh & Mian, 2006; C. W. Park & Stice, 2000), accuracy and information content are not two sides of the same coin, as the factors driving forecast accuracy and information content can be different (Clement & Tse, 2003). Thus, studies on analyst expertise commonly examine both forecast accuracy and market reaction (De Franco & Zhou, 2009; Gu & Xue, 2008; Kumar, 2010). Hilary and Shen (2013) find that observing more management forecasts is related to more informative forecasts. Similarly, Bradley et al. (2017) find forecast revisions issued by analysts with pre-industry experience evoke stronger market reactions. Taken together, prior evidence indicates that analysts' expertise in specific areas is associated with enhanced forecast accuracy and informativeness.

This study focuses on analysts' ESG expertise because ESG information has become an important form of information in capital markets. Prior studies find that asset prices react to ESG news, e.g., Flammer (2013), Krüger (2015), and Capelle-Blancard & Petit (2019), because ESG information can provide critical insights into both risks and opportunities. Regarding risks, ESG information reflects firms' exposure to long-term, non-diversifiable risks, such as climate change and reputational damage, which can influence firm valuation and portfolio performance (Bolton & Kacperczyk, 2023; Hong et al., 2019; Ilhan et al., 2021; Krueger et al., 2010; Venturini, 2022). In terms of opportunities, strong ESG performance often indicates sustainable competitive advantages, innovation, or alignment with societal trends. Therefore, from an asset pricing perspective, investors can use ESG information to manage risks and identify opportunities by integrating ESG factors into financial analysis, valuation, portfolio construction, and stewardship activities (PRI, 2023).

However, the evidence on whether ESG performance is associated with higher or lower returns is mixed. While some studies show ESG strategies yield superior risk-adjusted returns (Kempf & Osthoff, 2007; Statman & Glushkov, 2009), others suggest neutral or negative effects (de Haan et al., 2012; Hartzmark & Sussman, 2019; Hong & Kacperczyk, 2009; Managi et al., 2012). Recent studies propose frameworks to reconcile the mixed evidence, considering the ESG's impact on profitability, long-term risk, and investors' different and shifting ESG preferences (Pástor et al., 2021, 2022; Pedersen et al., 2021). Therefore, while ESG information is useful, it is complicated and challenging for investors to integrate into their investment decisions.

Similarly, ESG information has been demonstrated to be informative for financial analysts (Dhaliwal, Li, Tsang, & Yang, 2011; Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012). Recent research shows that analysts incorporate various ESG-related information, including climate risk, weather shocks, and temperature extremes, into their earnings forecasts, stock recommendations, and discussion in their research reports (Addoum, Ng, & Ortiz-Bobea, 2023; Cuculiza, Kumar, Xin, & Zhang, 2021; Faralli, 2023; M. Park, Yoon, & Zach, 2022). However, research and survey evidence highlight the challenges of using ESG information. For example, Amel-Zadeh and Serafeim (2018) find that, in a survey of mainstream investment organizations, respondents consider that the top three impediments to integrating ESG information are: lack of comparability across firms, lack of reporting standards, and the cost of gathering and analyzing information. Practitioners responding to a survey by the CFA Institute expressed concerns about greenwashing and materiality (CFA, 2018). Addoum et al. (2023) find that analysts' response to inter-quarter temperature shocks is slow, suggesting the need for more guidance to help analysts incorporate climate-related information promptly.

One challenge for analysts in incorporating ESG information into financial forecasts arises from the uncertain relationship between ESG performance and firm value. Under the strategic view, ESG performance provides benefits to firms, such as better access to finance (Cheng et al., 2014), more favorable media coverage (Cahan, Chen, Chen, & Nguyen, 2015), and higher stock returns during the financial crisis (Lins et al., 2017). On the other hand, under the agency view, ESG performance may benefit managers rather than shareholders (Masulis & Reza, 2015).

Moreover, as ESG performance is not unidimensional, the influence of ESG performance may vary depending on specific issues and industries. Khan et al. (2016) consider materiality and find that the stock returns for firms with good ratings on material ESG issues outperform

those with poor ratings; however, the relation between ratings and performance is not significant for immaterial issues. Hence, processing ESG information requires that the analyst is able to understand the subtleties of ESG performance and determine whether a particular aspect of ESG performance affects firm value. Further, once an aspect is determined to be value-relevant, the analyst must decide how to incorporate that information into their valuation models. For example, they could integrate ESG information by adjusting risk factors, growth rates, revenues, or expenses, which also requires judgment.

Adding to this complexity, significant divergences among ESG ratings further complicate analysts' tasks (Chatterji, Durand, Levine, & Touboul, 2016; Dorfleitner, Halbritter, & Nguyen, 2015). ESG divergences stem from variations in measures, scopes, and weights applied by different rating agencies (Berg, Koelbel, & Rigobon, 2022; Christensen, Serafeim, & Sikochi, 2022). Evidence shows that the divergence creates obstacles for investors including analysts in incorporating ESG news into stock valuation (Gibson Brandon, Krueger, & Schmidt, 2021; Serafeim & Yoon, 2021).

Given the complexity of understanding and incorporating ESG information into analysts' formal models and qualitative judgements, consistent with the learning-by-doing model and research on task-specific knowledge, we expect that analysts who have more experience and exposure to ESG information (i.e., a greater extent of expertise) will be able to use ESG information more effectively than analysts who are less familiar with ESG information.[3]

However, it is possible that ESG expertise might not be associated with more effective use of ESG information. ESG information is non-financial in nature and encompasses a multitude of corporate responses, ranging from human rights to environmental protection. As such, expertise gained from exposure to ESG information of one firm might not be transferrable to other firms. Said differently, if the mapping of ESG activities to future cash flows differs across firms (i.e., has different payoffs), ESG information can be highly idiosyncratic at the firm level.

ESG expertise equips analysts with the ability to incorporate material ESG factors into their analyses, which can improve their outputs. While there may be challenges due to the complexity of ESG information, we expect that the benefits of ESG expertise will outweigh these challenges, leading to improved forecast accuracy and greater revision informativeness. There are two main reasons. First, our study focuses on industry-specific ESG expertise, which is more likely to be transferable and relevant than general ESG exposure, as ESG issues are more similar within industries.[4] Second, since third-party ESG ratings provide a standardized assessment of ESG performance, they may help mitigate comparability issues and facilitate analysts' learning-by-doing. Therefore, we hypothesize:

H1. *Analysts with greater ESG expertise have higher forecast accuracy.*

H2. *Analysts with greater ESG expertise produce more informative forecast revisions.*

[3] While certain ESG issues are more material and have a greater impact on corporate financial performance than others, we consider ESG expertise to encompass both the ability to incorporate material issues and the skill to distinguish between material and immaterial issues. For instance, an inexperienced analyst may misjudge the relevance of ESG factors, potentially overestimating the impact of immaterial issues or underestimating the significance of material ones on financial performance.

[4] This view is supported by industry-level ESG standards developed by frameworks such as the Sustainability Accounting Standards Board (SASB) and the Global Reporting Initiative (GRI), which are based on the premise that material ESG factors are often industry-specific.

2.2. ESG expertise

In the spirit of Clement et al. (2007) and Hilary and Shen (2013), we measure ESG expertise based on an analyst's exposure to firms with ESG ratings in the past five years. Prior evidence shows that ESG information is informative to analysts (Bernardi & Stark, 2018; Dhaliwal et al., 2011; Dhaliwal et al., 2012) and is widely considered by investors (Amel-Zadeh & Serafeim, 2018). Among various sources of ESG information, we focus on third-party ESG ratings. Serafeim and Yoon (2022) find that ESG ratings predict future ESG news and proxy for market expectations of future news, providing evidence that ESG ratings are informative. Compared to other sources of ESG information such as corporate sustainability reports, third-party ratings reduce two of the top three barriers to using ESG information as ranked by investors in Amel-Zadeh and Serafeim (2018), i.e., lack of comparability across firms and the cost of gathering and analyzing ESG information. Therefore, time-constrained analysts may rely on third-party ratings to collect relatively uniform ESG data across a wider set of firms.[5] Among the ESG ratings, we use Sustainalytics for our main analysis. According to the survey and interviews conducted by SustainAbility by ERM, investors consider Sustainalytics ratings as the most useful out of ten ESG ratings.[6]

We begin at the analyst-year level and compute *ESG exposure* as the cumulative number of firms in an analyst's portfolio with ESG ratings over the past five years.[7] Considering variations in ESG factors across industries, we calculate *industry ESG exposure* and *non-industry ESG exposure*. The *industry ESG exposure* (*non-industry ESG exposure*) is equal to the number of firm-years with an ESG rating in the five prior years that are (not) in the same two-digit SIC industry as the forecasted firm. Since Sustainalytics data are available from 2009 and calculating ESG expertise requires at least one past year of data, our sample period is from 2010 to June 2018.

Because analysts covering more firms and with longer experience are likely to have broader exposure to ESG ratings, ESG exposure is often correlated with broader exposure to general firm information. To disentangle the specific effects of ESG expertise from the broader effects of general coverage patterns, we adjust the effects of general coverage using an orthogonalization process:

$$Industry\ ESG\ exposure_{ijt} = \alpha + \beta_1 Industry\ coverage_{ijt} + \beta_2 General\ coverage_{ijt} + \varepsilon_{ijt} \quad (1)$$

$$Non-industry\ ESG\ exposure_{ijt} = \alpha + \beta_1\ Industry\ coverage_{ijt} + \beta_2\ General\ coverage_{ijt} + \varepsilon_{ijt} \quad (2)$$

where *Industry coverage* (or *General coverage*) is the cumulative number

[5] Although some analysts may gain ESG expertise by processing ESG information from other sources such as corporate disclosures and media news, it is difficult to measure this effort using archival data. Moreover, the information contained in corporate disclosures and media news is largely captured by the ESG rating agencies. For example, Sustainalytics has news monitoring which collect news information from over 60,000 media sources. See https://www.sustainalytics.com/esg-data.

[6] ERM (Environmental Resources Management) is the largest pure-play sustainability consultancy. The survey report is available at https://www.sustainability.com/thinking/rate-the-raters-2020/. Another two ratings that are commonly used in academic studies, Bloomberg and ASSET4, rank sixth and eighth, respectively. Also, as shown on Sustainalytics website, Sustainalytics' clients include 19 out of top 20 asset managers (refer to https://www.sustainalytics.com/about-us.). In sensitivity tests described in section 2.5.1., we construct an alternative measure of ESG expertise based on the ASSET4 ratings.

[7] The cumulative number of firms means that if firm *j* has Sustainalytics ratings in year *t*-1 and year *t*-2, and analyst *i* covers firm *j* in *t*-1 and *t*-2, firm *j* will be counted twice when calculating analyst *i*'s ESG exposure in year *t*.

of firm-years in an analyst's portfolio within (or outside) the same two-digit SIC industry as firm *j* over the prior five years, regardless of ESG ratings. We use the residuals from eqs. (1) and (2) as our measure of industry ESG expertise (*Ind ESG Exp*) and non-industry ESG expertise (*Non-ind ESG Exp*), respectively. The residuals capture the portion of raw ESG expertise not explained by general expertise and isolate the ESG expertise.

2.3. Research design and data

We obtain data from several sources. We use ESG performance ratings from Sustainalytics for the period between 2009 and 2018 for our primary tests. We also use ESG related data from LSEG (formerly Refinitiv) ASSET4, MSCI KLD, and Bloomberg in additional tests. We collect analysts' annual forecasts from the Institutional Broker Estimate System (I/B/E/S) detail history from January 1990 to June 2018.[8] Analyst-level variables are calculated based on forecasting data during this period. Stock market data (including stock price and stock return) are obtained from CRSP. Firms' financial data are extracted from Compustat.

We first examine H1, which is a null hypothesis that posits that ESG expertise is related to analysts' forecast accuracy. Following prior studies (Bradley et al., 2017; Clement, 1999; Malloy, 2005), we estimate the following model:

$$PMAFE_{ijkt} = \alpha + \beta_1 Ind\ ESG\ Exp_{ijkt} + \beta_2 Non-ind\ ESG\ Exp_{ijkt} + controls + \varepsilon_{ijkt} \quad (3)$$

In eq. (3), the forecasting performance measure is the proportional mean absolute forecast error ($PMAFE_{ijkt}$) of analyst *i*'s annual earnings forecast for firm *j* for year *t* issued at date *k* and is defined as follows:

$$AFE_{ijkt} = Abs\left(Forecast\ EPS_{ijkt} - Actual\ EPS_{jt}\right) \quad (4a)$$

$$PMAFE_{ijkt} = \left(AFE_{ijkt} - MAFE_{jt}\right)/MAFE_{jt} \quad (4b)$$

where AFE_{ijkt} is the absolute forecast error for analyst *i*'s annual earnings forecast of firm *j* for year *t* issued at date *k* and $MAFE_{jt}$ is the mean absolute forecast error for firm *j* for year *t*. *PMAFE* was developed by Clement (1999) and measures relative forecast accuracy. As constructed, a smaller *PMAFE* indicates a smaller relative forecast error and greater forecast accuracy.

The variable of interest is *Ind ESG Exp*. Following prior studies (e.g., Bradley et al., 2017; Clement, 1999), we include a host of analyst-level and firm-level control variables. To further control for analysts' past experience, we include the number of years since analyst *i* first provided forecasts in IBES to control for general experience (*Gen Exp*) and the number of years since analyst *i* first provided forecasts for firm *j* in IBES to control for firm-specific experience (*Firm Exp*).[9] As forecasts closer to the earnings announcement date tend to be more accurate, we control for the number of days between the analyst forecast issuance date and the earnings announcement date (*Horizon*). We also control the number of stocks and two-digit SIC industries followed by analyst *i* (*Port Size* and *Num SIC2*, respectively) and whether analyst *i* is from a top 10% brokerage house (*Top 10*) to account for analysts' busyness and resources available. All the above-mentioned variables are mean-adjusted at the firm-year level because, as explained in Clement (1999), controlling for firm-year effects can increase the likelihood of identifying differences in analysts' forecast accuracy compared to models that control firm and year fixed effects.

Table 1
Summary statistics.

Panel A: Unadjusted analyst characteristics

Variable	Mean	Q1	Median	Q3	Std. Dev.
AFE	0.44	0.05	0.14	0.38	1.12
Ind ESG Exp	11.31	0.00	5.00	17.00	14.35
Non-ind ESG Exp	8.67	0.00	2.00	12.00	13.54
Gen Experience	9.40	5.00	9.00	13.00	6.08
Firm Experience	4.24	1.00	3.00	6.00	4.29
Horizon	171.90	72.00	164.00	254.00	105.50
Port Size	18.70	13.00	18.00	23.00	8.63
Num SIC2	3.55	2.00	3.00	5.00	2.36
Top 10	0.67	0.00	1.00	1.00	0.47
Panel B: Mean-adjusted analyst characteristics					
Variable	Mean	Q1	Median	Q3	Std. Dev
PMAFE	−0.01	−0.61	−0.15	0.38	0.88
Ind ESG Exp	0.28	−3.14	0.15	3.42	6.69
Non-ind ESG Exp	0.45	−2.50	0.57	3.25	6.92
Gen Experience	0.30	−3.87	−0.18	3.82	5.62
Firm Experience	0.18	−2.34	−0.28	2.01	3.76
Horizon	3.00	−90.37	1.33	87.08	102.6
Port Size	0.34	−4.24	−0.21	4.29	7.39
Num SIC2	0.04	−0.88	−0.18	0.74	1.62
Top 10	0.00	−0.48	0.18	0.32	0.44
Panel C: Firm characteristics					
Variable	Mean	Q1	Median	Q3	Std. Dev
Cover	20.66	11.00	19.00	28.00	11.53
Size	8.46	7.29	8.45	9.68	1.78
BP	0.53	0.24	0.42	0.71	0.63
ROA	0.01	0.01	0.04	0.08	0.85
Loss	0.21	0.00	0.00	0.00	0.41
Age	24.99	12.00	21.00	36.00	16.92
Ret	0.15	−0.09	0.11	0.31	0.49
ESG Expert Cover	11.34	4.00	9.00	18.00	10.73
ESGP	53.58	47.00	51.00	59.00	8.37

This table reports summary statistics. Panel A presents descriptive statistics for the unadjusted analyst characteristics. Panel B presents descriptive statistics for the mean-adjusted analyst characteristics at the firm-year level. Panel C presents descriptive statistics for firm characteristics. Statistics of ESG Expert Cover and ESGP are calculated using firm-year level sample. Statistics of the other variables are calculated using analyst-firm-year-forecast level sample.

In addition to analyst-level controls, we include firm-level controls including firm size measured by the natural log of market capitalization (*Size*), book-to-market ratio (*BP*), return-on-asset (*ROA*), loss indicator (*Loss*), number of analysts following firm *j* (*Cover*), firm age (*Age*), and firm *j*'s return over the past twelve months (*Ret*).

H2 is a null hypothesis that predicts that ESG expertise is related to a stronger market reaction to analysts' forecast revisions. Following Clement and Tse (2003) and others, we estimate the following model:

$$CAR_{ijkt} = \alpha + \beta_1 Revision_{ijkt} + \beta_2 Ind\ ESG\ Exp_{ijkt} \times Revision_{ijkt} + \beta_3 Non-ind\ ESG\ Exp_{ijkt} \times Revision_{ijkt} + \beta_4 Ind\ ESG\ Exp_{ijkt} + \beta_5 Non-ind\ ESG\ Exp_{ijkt} + controls + \varepsilon_{ijkt} \quad (5)$$

The dependent variable is the cumulative abnormal DGTW-adjusted return (CAR_{ijkt}) in the three-day window around earnings forecast issuance date [−1,+1] (Daniel, Grinblatt, Titman, & Wermers, 1997). Revision is the magnitude of forecast revision measured by the difference between analyst *i*'s forecast for firm *j* year *t* at time *k* and the previous forecast at time *k*-1 scaled by the absolute value of the previous forecast at *k*-1 (Ivković & Jegadeesh, 2004). If the revisions are

[8] We use I/B/E/S data up to 30 June 2018 before the major I/B/E/S forecast data change effective from October 18, 2018. Changes include but are not limit to (1) 30.7% of all analyst IDs (ANALYS) have been reassigned and (2) estimates data from UBS Equities have been removed. See https://wrds-www.wharton.upenn.edu/ documents/1030/Product_Change_Notification-IBES_Detail_History-_PreApproval_Contributor.pdf.

[9] The results remain similar when including analysts' industry experience as an additional control.

Table 2
Correlation matrix for main mean-adjusted analyst characteristics.

	PMAFE	*Ind ESG Exp*	*Non-ind ESG Exp*	*Gen Exp*	*Firm Exp*	*Horizon*	*Port Size*	*Num SIC2*	*Top 10*
PMAFE	1								
Ind ESG Exp	−0.017***	1							
Non-ind ESG Exp	−0.013***	0.119***	1						
Gen Exp	−0.025***	0.015***	0.014***	1					
Firm Exp	−0.028***	0.016***	0.010***	0.561***	1				
Horizon	0.364***	−0.027***	−0.061***	−0.028***	−0.032***	1			
Port Size	−0.010***	−0.023***	0.036***	0.249***	0.120***	−0.016***	1		
Num SIC2	0.002*	0.002*	−0.007***	0.138***	0.050***	−0.002**	0.544***	1	
Top 10	0.00100	0.071***	0.036***	−0.053***	−0.015***	−0.004***	0.116***	−0.003***	1

See Appendix A for variable definitions.

informative to investors, the coefficient of *Revision* (β_1) is expected to be positive. If the market reacts more strongly to forecast revisions issued by analysts with high industry ESG expertise, the coefficient of *Ind ESG Exp*×*Revision* (β_2) is expected to be positive. In addition to control variables in eq. (3), we include *LagPMAFE*, which is the PMAFE of analyst *i*'s most recent forecast for firm *j* for year *t*-1. The most recent forecast is defined as the last forecast with a minimum forecast horizon of 30 days and issued in the first 11 months of fiscal years (Clement, 1999).

Our sample starts with 1,513,117 annual earnings forecasts. Following Clement (1999) and Clement et al. (2007), we require at least two analysts to issue forecasts for a firm within a given year to calculate the mean-adjusted analyst-level variables. After removing observations with missing data for analyst- or firm-level variables in eq. (3), the final sample for the regressions on forecast accuracy includes 7070 analysts issuing 1,250,009 annual earnings forecasts for 4676 unique firms. The sample size may vary depending on the specific model.

2.4. Summary statistics and correlations

Table 1 Panels A and B summarize the main variables used in eqs. (3). All continuous variables are winsorized at 0.5% and 99.5%.[10] Panel A provides summary statistics for unadjusted main analyst characteristics. On average, in the past five years, analysts in our sample issue forecasts for 11.31 (8.67) firm-years for firms that have Sustainalytics ratings and that are (not) in the same industry as the forecasted firm. *Ind ESG Exp* is larger than *Non-ind ESG Exp*, which aligns with the common practice among analysts to focus their coverage within specific industries, resulting in more concentrated portfolios. Panel B reports summary statistics for mean-adjusted analyst characteristics at the firm-year level. After mean-adjusting, the means and medians are closer to zero.

Table 2 presents Pearson correlations for the mean-adjusted analyst characteristics in eq. (3). The correlation between *PMAFE* and raw industry ESG expertise is negative as predicted. The relatively high correlations between the two raw ESG expertise measures and analysts' mean-adjusted general expertise (*Gen Exp*) are not surprising. As discussed in section 2.2., we orthogonalize ESG expertise and general expertise to ensure our ESG expertise measures are not correlated with general expertise.

2.5. Empirical results

2.5.1. ESG expertise and forecast accuracy (H1)

Table 3 reports the regression results for eq. (3) which considers the effects of ESG expertise on analyst forecast errors. The dependent variable is relative forecast errors (*PMAFE*). While our variable of interest is industry ESG expertise (*Ind ESG Exp*), we also include non-industry ESG expertise (*Non-ind ESG Exp*) as a control variable.

Columns (1)–(3) show that the coefficient of *Ind ESG Exp* is negative and significant at the 1% level regardless of analyst-level and firm-level controls, indicating that analysts with ESG expertise in the same industry issue more accurate earnings forecasts. On the other hand, the coefficient of *Non-ind ESG Exp* is negative and significant in Column (1) when there are no other controls. It becomes positive and significant when analyst-level controls are added in Columns (2) and (3), suggesting potential confounding effects with other analyst characteristics.

One possible explanation is that effective ESG integration is highly industry-specific. ESG factors that are material and relevant vary considerably across sectors (e.g., Khan et al., 2016). Analysts with non-industry ESG expertise may apply generalized frameworks or heuristics that do not align with the ESG risks and opportunities most salient to the focal industry. For example, environmental concerns may be financially critical in the energy sector but largely immaterial in the technology sector. If analysts interpret ESG data based on patterns from different industries, they may underestimate or overestimate the effects of ESG issues on firms' financial performance. Prior literature highlights the importance of industry specialization for analyst performance (Bradley et al., 2017; Jacob et al., 1999), further supporting this view.

Our data shows that industry switching is not uncommon. We check the two-digit SIC industries covered by one analyst in a specific year. We find that in 20.7% of cases (21,982 out of 106,080 analyst-industry-year observations), the analyst did not cover the same industry in the previous year. In such cases, prior ESG expertise from other industries may reduce forecast quality before new industry-specific knowledge is developed.

Another possible explanation is limited attention. Prior studies show that analysts face cognitive constraints when processing complex information (Driskill, Kirk, & Tucker, 2020; Hirst, Hopkins, & Wahlen, 2004). On average, analysts in our sample cover 3.55 two-digit SIC industries annually (Table 1), indicating that multi-industry coverage is common. While analysts covering more industries may have broader ESG exposure and be more aware of ESG issues in general, they may lack the depth of industry-specific knowledge required to assess the financial implications of ESG risks and opportunities. This may result in greater attention to ESG issues but less precise incorporation of those issues into forecasts.

However, it is also possible that the broader scope of non-industry ESG exposure could overwhelm analysts' cognitive resources. They may spend less time and effort analyzing the ESG information for individual firms. These results suggest that while ESG expertise is important, it is only the ESG expertise associated with the forecasted firm's industry that improves the analyst's forecasting skills.

We further conduct cross-sectional analyses on industry switching, coverage breadth, and workload (untabulated). First, the effects of industry-specific and non-industry ESG expertise are statistically similar between high- and low-switch analysts, suggesting that switching does

[10] The results are statistically similar if variables are winsorized at 1% and 99%.

Table 3
Regressions of forecast accuracy on ESG expertise.

Variable	(1)	(2)	(3)	(4)
Ind ESG Exp	**−0.0021*** **	**−0.0011*** **	**−0.0011*** **	**−0.0041*** **
	(−5.33)	**(−3.05)**	**(−3.04)**	**(−6.58)**
Non-ind ESG Exp	−0.0014***	0.0014***	0.0014***	0.0025***
	(−5.01)	(5.15)	(5.12)	(7.20)
Gen Exp		−0.0013***	−0.0013***	−0.0015
		(−2.59)	(−2.61)	(−1.26)
Firm Exp		−0.0028***	−0.0028***	−0.0067***
		(−5.21)	(−5.19)	(−4.05)
Horizon		0.0032***	0.0032***	0.0032***
		(93.85)	(93.85)	(93.86)
Port Size		−0.0006	−0.0006	−0.0008
		(−0.71)	(−0.72)	(−1.60)
Num SIC2		0.0038*	0.0038*	0.0052***
		(1.80)	(1.80)	(2.66)
Top 10		0.0060	0.0060	0.0027
		(1.22)	(1.22)	(0.40)
Cover			0.0001	−0.0010*
			(0.21)	(−1.87)
Size			−0.0011	−0.0022
			(−0.93)	(−0.58)
BP			−0.0028	−0.0137***
			(−1.54)	(−4.50)
ROA			−0.0002	0.0019**
			(−0.98)	(2.34)
Loss			−0.0006	0.0064
			(−0.18)	(1.23)
Age			−0.0002**	−0.0011
			(−2.07)	(−1.31)
Ret			0.0075***	0.0065*
			(2.74)	(1.84)
Constant	−0.0051**	−0.0152***	−0.0025	0.0579
	(−2.21)	(−6.89)	(−0.38)	(1.49)
N	1,250,009	1,250,009	1,250,009	1,242,958
R^2	0.0004	0.137	0.137	0.281
Analyst-firm FE	N	N	N	Y

This table presents the regression of analysts' forecast accuracy on industry ESG expertise, i.e., eq. (3). The dependent variable is the proportional mean absolute forecast error (*PMAFE*) defined as the difference between absolute forecast error of analyst *i* for firm *j* for year *t* issued at date *k* 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 industry ESG expertise [*Ind ESG Exp*] derived from eqs. (1) and (2). See Appendix A for variable definitions. Analyst-firm fixed effects are included in columns (4) to control for analysts' innate ability. Robust standard errors doubled-clustered at the firm and analyst levels are used to compute the *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

not drive the result.[11] Second, we find that analysts who cover more industries exhibit a weaker adverse association between non-industry ESG expertise and forecast accuracy, consistent with broader exposure facilitating learning. Third, heavier analyst workload, proxied by the number of forecasts issued during the year, amplifies the negative effect of non-industry ESG expertise, indicating that limited attention reduces analysts' capacity to contextualize ESG information acquired outside the focal industry. While the tests identify attention and learning as contributing factors, future research could further examine industry-level differences in ESG materiality, for example, whether a mismatch between an analyst's prior ESG learning and the material ESG issues of the focal industry exacerbates forecast performance.

Following Clement et al. (2007), we add analyst-firm fixed effects to control for analysts' innate ability. The results reported in Column (4) are consistent. The annual earnings forecasts of analysts at the 75th percentile of industry-specific ESG expertise are 2.69% more accurate than those of analysts at the 25th percentile. In comparison, Bradley et al. (2017) find that the annual earnings forecasts of analysts with pre-analyst industry experience provide forecasts that are 3.58% more accurate than those of inexperienced analysts. Therefore, while the impact of analysts' industry ESG expertise is lower than that of pre-analyst industry experience, it is still comparable in magnitude.[12]

To tighten the link between ESG ratings and analysts' forecast accuracy, we create an indicator, *Has Rating*, that is equal to one if the firm has an ESG rating from Sustainalytics in year *t*, and zero otherwise. Then, we interact *Has Rating* with *Ind ESG Exp* and find that the coefficient for the interaction is negative and significant at the 5% level (Appendix C.1. Column (1)), indicating that the forecast accuracy for analysts with industry ESG expertise is more precise when the forecasted firm is rated by Sustainalytics, consistent with analysts learning from this rating. We repeat this analysis but instead, code *Has Rating* one if the firm has an ESG rating from Bloomberg or ASSET4. The results (Appendix C.1. Columns (2) and (3)) indicate that the coefficient for the interaction remains negative and significant, meaning our results are robust to different sources of ESG ratings.[13,14]

We conduct several tests to assess the robustness of our baseline results. In Table 3, we include all analyst forecasts issued before the earnings announcement as this enables a comparison of analysts' forecast accuracy over the whole forecasting period within our sample period. A similar sampling is used in prior studies, e.g., Kumar (2010) and De Franco and Zhou (2009). On the other hand, some other studies use the most recent forecast in the forecasting period (e.g., Clement, 1999; Clement et al., 2007). The rationale is that with the most information available, the last forecast should be the most accurate forecast that an analyst could achieve. Following Clement et al. (2007), we retain the last forecasts for each analyst-firm-year pairing that are (1) within a minimum forecast horizon of 30 days and (2) issued within the first 11 months of the fiscal year. Column (1) of Table 4 reveals that the coefficient of industry ESG expertise remains negative and significant.

Next, we restrict the sample to analysts with ESG expertise. Specifically, we exclude analysts following no firms with a Sustainalytics rating. Column (2) shows that *Ind ESG Exp* continues to have a negative and significant coefficient. Column (3) considers whether ESG expertise is still important for analysts with at least five years of general experience as seasoned analysts may accumulate ESG knowledge over time. The results are similar to the baseline model which indicate that even among analysts who are more advanced in their careers, industry ESG expertise makes a difference. To examine the generalizability across rating agencies, we measure ESG expertise using alternative ESG ratings, LSEG ASSET4 ratings, in place of Sustainalytics ratings. Column (4) reveals that the coefficient of *Ind ESG Exp* remains negative and significant at the 1% level. Taken together, these results are consistent with Hypothesis 1, which predicts that industry ESG expertise improves the

[11] We measure number of years with industry switch. For each analyst-year, we form the set of all two-digit SIC industries the analyst covered that year. We code an analyst-year as "switch" when this year's set is not the same as last year's, i.e., at least one industry is newly added or dropped.

[12] Because the ESG expertise variables in Eq. (3) are generated from first-stage regressions (Eqs. (1) and (2)), conventional standard errors may not fully account for first-stage estimation uncertainty. We assess inference using a full two-stage cluster bootstrap that resamples analysts with replacement and re-estimates both stages in each replication. Untabulated inference based on 1000 bootstrap replications remains similar.

[13] We notice that Sustainalytics and ASSET4 significantly increased their coverage in 2016. This aligns with the growing global emphasis on sustainability during this period. Despite this variation, we find no significant differences in results before and after 2016.

[14] We also consider the potential impact of ESG rating divergence on the relationship between ESG expertise and forecast accuracy. We calculate ESG divergence as the standard deviation of ESG ratings from Sustainalytics, ASSET4, and KLD. However, we find no significant moderating effects.

Table 4
Robustness tests for ESG expertise and forecast accuracy.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Ind ESG Exp	**−0.0039*** **	**−0.0050*** **	**−0.0035*** **	**−0.0023*** **	**−0.0042*** **	**−0.0044*** **
	(−4.97)	**(−8.58)**	**(−5.00)**	**(−5.70)**	**(−9.06)**	**(−11.67)**
Non-ind ESG Exp	0.0009**	0.0034***	0.0023***	0.0024***	0.0037***	0.0039***
	(2.12)	(8.19)	(6.95)	(6.06)	(8.70)	(11.27)
Gen Exp	−0.0001	−0.0013	−0.0018	−0.0017	−0.0015	−0.0014
	(−0.06)	(−1.17)	(−1.63)	(−1.48)	(−1.33)	(−1.20)
Firm Exp	0.0052*	−0.0077***	−0.0075***	−0.0070***	−0.0064***	−0.0044***
	(1.90)	(−4.31)	(−4.84)	(−3.89)	(−3.74)	(−2.68)
Horizon	0.0026***	0.0032***	0.0033***	0.0032***	0.0032***	0.0032***
	(62.17)	(86.22)	(97.79)	(93.80)	(94.02)	(94.29)
Port Size	−0.0003	−0.0007	−0.0002	−0.0006	−0.0005	−0.0004
	(−0.37)	(−1.14)	(−0.41)	(−1.05)	(−0.92)	(−0.61)
Num SIC2	0.0038	0.0049**	0.0035*	0.0052***	0.0034*	0.0020
	(1.35)	(2.12)	(1.70)	(2.66)	(1.74)	(1.00)
Top 10	−0.0108	0.0017	0.0033	0.0038	0.0029	0.0037
	(−1.31)	(0.23)	(0.49)	(0.56)	(0.43)	(0.54)
Cover	−0.0006	−0.0013**	−0.0005	−0.0009	−0.0010*	−0.0013**
	(−0.62)	(−2.10)	(−0.91)	(−1.53)	(−1.73)	(−2.28)
Size	−0.0063	0.0007	−0.0003	−0.0023	−0.0027	−0.0054
	(−0.96)	(0.14)	(−0.07)	(−0.59)	(−0.70)	(−1.41)
BP	−0.0058	−0.0162***	−0.0167***	−0.0137***	−0.0136***	−0.0137***
	(−1.57)	(−4.93)	(−6.20)	(−4.48)	(−4.50)	(−4.53)
ROA	0.0041***	0.0008	0.0030**	0.0018**	0.0018**	0.0020**
	(3.22)	(0.51)	(2.19)	(2.25)	(2.24)	(2.48)
Loss	0.0166	0.0084	0.0026	0.0066	0.0065	0.0038
	(1.50)	(1.41)	(0.51)	(1.25)	(1.23)	(0.73)
Age	0.0014	−0.0025**	−0.0020**	−0.0021*	−0.0012	0.0009
	(0.83)	(−2.13)	(−2.11)	(−1.89)	(−1.28)	(1.02)
Ret	−0.0101	0.0046	0.0006	0.0061*	0.0064*	0.0072**
	(−1.60)	(0.96)	(0.18)	(1.74)	(1.82)	(2.08)
Constant	−0.1175*	0.0773	0.0619	0.0804*	0.0631	0.0447
	(−1.74)	(1.56)	(1.60)	(1.81)	(1.53)	(1.15)
N	257,693	1000,481	1,108,585	1,242,958	1,242,958	1,242,958
R^2	0.420	0.279	0.268	0.281	0.281	0.282
Analyst-firm FE	Y	Y	Y	Y	Y	Y

This table presents results of robustness test for eq. (3). The dependent variable is the proportional mean absolute forecast error (*PMAFE*). Column (1) presents the regression result for the most recent forecasts defined as the last forecast issued by analyst *i* for firm *j* for year *t* that (1) were issued at least 30 days before earnings announcement and (2) were issued during the first 11 months of the year through year *t*. Column (2) presents the regression result for the sample excluding those analysts who do not cover any firms with Sustainalytics ratings. Column (3) presents the result for experienced analysts with no less than five years of general experience. Column (4) presents the result for ESG expertise measured by ASSET4 ratings. Both ESG expertise measures are calculated in the same way as ESG expertise measured by Sustainalytics ratings. Column (5) presents the result for raw ESG expertise (i.e. *ESG exposure*). Column (6) presents the result for ESG measures calculated based on the sample up to the current year. See Appendix A for variable definitions. Analyst-firm fixed effects are included to control for analysts' innate ability. Robust standard errors doubled-clustered at the firm and analyst levels are used to compute *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

forecast accuracy of sell-side analysts.[15]

To exclude the possibility that the finding may result from orthogonalization, we performed analyses using raw ESG exposure (i.e., without orthogonalization). Column (5) shows that the results remain consistent, indicating that analysts with more exposure to industry ESG information are more accurate. Furthermore, to address potential look-ahead bias, we re-estimated ESG expertise measures using data available up to each observation year. This approach ensures that future information does not influence the measurement of ESG expertise. The result in Column (6) is consistent with the baseline findings.

2.5.2. ESG expertise and stock price reaction (H2)

Table 5 reports the results for testing the effect of *Ind ESG Exp* on the market reaction to analysts' forecast revisions. Following Ivković and Jegadeesh (2004), *Revision* is defined as the difference between analyst *i*'s forecast for firm *j* for year *t* at time *k* and the previous forecast at time *k*-1 scaled by the absolute value of the forecast at time *k*-1. The denominator is set to 0.01 if lower, and values are multiplied by 100 and are truncated between −50% and 50%. Similar to prior studies (Bradley et al., 2017; Gleason & Lee, 2003; Ivković & Jegadeesh, 2004), we consider the direction of forecast revisions when examining the market reaction. We classify revisions above (below) an analyst's prior forecast as upward (downward) revisions.

Column (1) presents results for the short-term market reaction to upward revisions using a three-day window [−1, +1]. The coefficient of the interaction between revision and *Ind ESG Exp* is positive and significant at the 1% level, indicating that upward forecast revisions issued by analysts with higher industry ESG expertise generate a more pronounced short-term market reaction. In contrast, the interaction between revision and non-industry ESG expertise is not significant, suggesting that upward forecast revisions issued by analysts with non-industry ESG expertise are not more informative. Column (2) presents the result for the three-month buy-and-hold abnormal return ([−1,+63]

[15] Eq. (1) and (2) split ESG exposure into two components: the fitted values that are determined by the coverage patterns and the residual values that are unrelated to coverage patterns. We include the residual components only in our baseline models for presentation brevity. We conduct robustness checks where we include fitted values from Eqs. (1) and (2) and repeat the tests, the results remain similar.

Table 5
Regressions of market reactions to earnings forecast revisions and ESG expertise.

	Upward revisions		Downward revisions	
Variable	(1) CAR[−1,+1]	(2) BHAR[−1,+3 M]	(3) CAR[−1,+1]	(4) BHAR[−1,+3 M]
Revision	0.0375***	1.2008***	0.0342***	0.2382**
	(3.06)	(10.88)	(2.90)	(2.19)
Ind ESG Exp	−0.0129	−0.0474	−0.0083	0.0638
	(−1.16)	(−0.60)	(−0.63)	(0.69)
Revision*×*Ind ESG Exp	**0.0026*** **	**0.0172***	**−0.0020****	**−0.0040**
	(3.00)	**(1.92)**	**(−2.20)**	**(−0.71)**
Non-ind ESG Exp	0.0111	−0.0018	−0.0200*	0.0504
	(1.24)	(−0.03)	(−1.67)	(0.74)
Revision×*Non-ind ESG Exp*	−0.0001	−0.0138**	−0.0011	−0.0064
	(−0.15)	(−2.15)	(−1.16)	(−1.29)
LagPMAFE	−0.0742	−1.1520	0.1168	−0.3666
	(−0.74)	(−1.30)	(1.19)	(−0.47)
Gen Exp	0.0061	0.1179	−0.0061	−0.0441
	(0.43)	(1.31)	(−0.34)	(−0.44)
Firm Exp	0.0096	−0.0501	0.0030	−0.2950**
	(0.58)	(−0.43)	(0.15)	(−2.54)
Horizon	0.0040***	0.0127	0.0007	−0.0574***
	(3.22)	(1.15)	(0.49)	(−4.29)
Port Size	0.0252*	0.0414	−0.0070	−0.0451
	(1.87)	(0.61)	(−0.48)	(−0.55)
Num SIC2	−0.0803*	−0.7425**	−0.0341	−0.0866
	(−1.83)	(−2.54)	(−0.63)	(−0.28)
Top 10	−0.1848	1.3775	0.2343	−0.4730
	(−1.13)	(1.59)	(1.23)	(−0.47)
Cover	−0.1088***	−4.3268***	−0.0937**	−4.2468***
	(−2.71)	(−9.55)	(−2.27)	(−8.36)
Size	1.5308***	40.2311***	2.6663***	56.0017***
	(3.64)	(7.21)	(5.08)	(8.95)
BP	1.2689*	52.2757***	0.8875	49.9739***
	(1.69)	(4.59)	(1.03)	(4.06)
ROA	0.0099	1.9630	−0.2088**	−0.0411
	(0.06)	(1.26)	(−2.16)	(−0.04)
Loss	−0.2661	−4.1823	0.0160	−1.5854
	(−0.49)	(−0.72)	(0.03)	(−0.31)
Age	−0.0137	−0.8727	−0.0750	0.4856***
	(−0.16)	(−0.36)	(−0.62)	(2.64)
Ret	−3.7978***	−109.4692***	−4.4798***	−133.7831***
	(−9.66)	(−18.64)	(−9.24)	(−21.65)
Constant	−9.8245**	−234.3228**	−20.7517***	−433.0333***
	(−2.33)	(−2.40)	(−3.77)	(−7.45)
N	367,326	367,125	364,473	364,257
R^2	0.032	0.101	0.026	0.088
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

This table presents the regression analysis of market reactions to earnings forecast revisions on industry ESG expertise, i.e., eq. (5). The dependent variable is the cumulative abnormal return over the three-trading-day window around the forecast announcement (i.e., CAR[−1,+1]) for Columns (1) and (3). The dependent variable is the three-month buy-and-hold abnormal return (i.e., [−1,+63] trading days) for Columns (2) and (4). The variable of interest is the interaction term of revision and industry ESG expertise (*Revision*×*Related ESG Exp*). Columns (1) and (2) present the results for upward revisions (i.e., the forecast which is higher than the analyst's previous forecast for the same firm for the same year). Columns (3) and (4) present the results for downward revisions. See Appendix A for variable definitions. Firm fixed effects and year fixed effects are included. Robust standard errors doubled-clustered at the firm and analyst levels are used to compute *t*-statistics in parentheses. All coefficients are multiplied by 1000. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

trading days) after upward revisions. The coefficient of the interaction remains positive and significant. This result confirms that the stronger short-term (i.e., the three-day window) market reaction to upward revisions from analysts with higher industry ESG expertise is attributable to informativeness rather than overreaction.

Columns (3) and (4) present the results for downward revisions. Column (3) shows that the short-term market reactions to downward revisions from analysts with higher *Ind ESG Exp* are less pronounced, and this relation is significant at the 5% level. However, the coefficient is not significant for three-month buy-and-hold abnormal returns in column (4), suggesting that the weaker market reactions over the three-day window are due to underreaction.[16]

Taken together, in the short-term three-day window, the market reacts more strongly to upward revisions issued by analysts with industry ESG expertise but less strongly to their downward revisions. In the longer three-month window, the stronger market reaction to upward revisions persists, while no significant differences are found for downward revisions. These results indicate that ESG expertise enhances the informativeness of upward revisions but does not have a similar effect on downward revisions. Economically, the analysis of the three-month window indicates that an analyst with *Ind ESG Exp* at the 75th percentile, compared to the 25th percentile, evokes a 0.1% higher market return for upward revisions and a 0.03% lower market return for downward revisions, when the revisions are at their means. This represents a moderate 6.6% increase for upward revisions and a 1.8% decrease for downward revisions relative to the average returns of 1.50% and − 1.65%, respectively.[17] Given that analysts issue multiple forecast revisions per year, these effects accumulate and can influence the perceived value-added of analyst research. Nonetheless, the effects should be viewed as moderate in economic size.

We note that the reported return spreads should be interpreted as evidence of information content rather than as a blueprint for a profitable standalone trading strategy. The incremental return differences, such as the 0.1% (10 basis points) three-month spread for upward revisions, reflect non-trivial differences in how the market prices analysts' information. When considering practical feasibility, trading on forecast revisions would involve frequent turnover and transaction costs that would likely absorb a substantial portion of these spreads.[18] Accordingly, we view our findings as highlighting the relevance of ESG expertise for the informativeness and quality of analyst research, rather than as implying an independently implementable trading rule.

While the findings indicate that ESG expertise enables analysts to contextualize positive information more effectively, the precise mechanism through which it translates into practitioner value remains unclear. For example, ESG expertise may influence how analysts frame their revisions, the extent to which they incorporate ESG-related cues into narrative discussions, or the credibility that investors attach to their positive signals. Identifying and distinguishing these channels goes beyond the scope of the current study, but we view this as a promising avenue for future research.

The different effects of ESG expertise on upward and downward forecast revision informativeness are consistent with findings from prior studies (Mikhail et al., 1997; Stickel, 1992, 1995). For instance, Mikhail et al. (1997) find that analysts' firm-specific experience is positively related to forecast accuracy. However, for more experienced analysts, the short-term market reactions are only stronger for their upward recommendation revisions to strong buys while the market reaction to their downward recommendation revisions is not significant. Mikhail et al. (1997) point out that a possible explanation is that analysts delay downward revisions (McNichols & O'Brien, 1997), and the delays are not related to analysts' experience. Consequently, the market may incorporate negative news before analysts revise downward.

We conduct multiple robustness checks. The results are reported in Appendix C.2. In the first test, to reduce the effects of forecasts issued by other analysts, we restrict the sample to forecasts that are the only forecast for firm *j* at date *k* to avoid potential confounding effects of forecasts from other analysts. In the second test, we exclude analysts with no ESG expertise to test the variations among analysts with ESG expertise. The third test restricts the sample to analysts with no less than five years of general experience. The fourth test uses ESG expertise measured by ASSET4 ratings. Overall, the results for these tests are all qualitatively similar to the results reported in Table 5 and show an asymmetric response to upward and downward revisions for analysts with industry ESG expertise.

3. Part II: ESG expertise and monitoring role

3.1. Background and hypothesis

In addition to analysts' information intermediary role, analysts play an important role in scrutinizing management and improving corporate governance (Jensen & Meckling, 1976). Several studies document evidence on analysts' monitoring role. For instance, Yu (2008) finds that analyst coverage is negatively related to earnings management. Using brokerage house mergers and closures as an exogenous shock to analyst coverage, Derrien & Kecskés (2013) document that a loss in analyst coverage is associated with a 1.9% decrease in investments. Similarly, Chen et al. (2015) find that a loss in analyst coverage deteriorates corporate governance, including lower marginal value of cash holdings, higher CEO excess compensation, less earnings management, and fewer value-destroying acquisitions. Furthermore, evidence shows that prior experience is critical for analysts' monitoring role. Yu (2008) finds that coverage by analysts with longer experience has a stronger effect on curbing earnings management. Bradley et al. (2017) find that firms covered by analysts with pre-industry experience manage earnings less, have fewer financial misrepresentations, less CEO excess compensation, and higher performance sensitivity of CEO turnover.

In contrast to the monitoring view, another strand of literature argues that analyst coverage could be detrimental as it represents external pressure. Under the pressure to meet analysts' forecasts, managers become myopic and cut spending that benefits their firm in the longer term. Irani and Oesch (2016) find that though analyst coverage reduces accrual-based earnings management, it increases real earnings management, which is more detrimental. Similarly, Winchel (2015) finds a positive relationship between analyst coverage and firms meeting or

[16] Because the ESG expertise variables in Eq. (5) are generated from first-stage regressions (Eqs. (1) and (2)), conventional standard errors may not fully account for first-stage estimation uncertainty. We use bootstrap as described in Footnote 12, the results (untabulated) remain similar. One minor difference is that the coefficient on Revision × Non-industry ESG Expertise in the BHAR [−1,+3 M] specification for positive forecast revisions becomes insignificant under the bootstrap, indicating that market reactions are primarily related to industry-specific ESG expertise.

[17] In the three-day window an analyst at the 75th percentile of *Ind ESG Exp* (vs. the 25th percentile) elicits a 0.015% higher return for upward revisions and a 0.014% lower return for downward revisions. The magnitude is smaller than longer term window as the average return over three-days window is lower than over the longer window.

[18] Transaction costs vary with stock liquidity, trade size, and execution method. For example, Jiang, Kim, and Zhou (2011) report a median effective bid-ask spread of 0.34% (34 basis points) for U.S. stocks. Turnover depends on the specific implementation (e.g., trading on all revisions versus only large-magnitude revisions by high-expertise analysts). Given the frequency of forecast revisions (15 revisions per analyst per year in our sample), trading on these signals is likely to entail non-trivial turnover and associated transaction costs that would likely absorb a substantial portion of the spreads.

beating analyst forecasts, suggesting firms are pressured to meet analysts' expectations. He and Tian (2013) find that firms covered by more analysts generate fewer patents and patents with lower impact.

In relation to ESG, the evidence is mixed. Adhikari (2016) finds that exogenous analyst coverage loss is associated with increased ESG performance, and this relationship can be partially explained by different levels of CEO ownership and corporate discretionary spending. He interprets ESG as an agency cost, and analysts act as external monitors and reduce the agency cost. Qian et al. (2019) find a relationship similar to Adhikari (2016), and the relationship is more pronounced for analysts from larger brokerage houses or with longer experience. They attribute the reason to external pressure as more prestigious analysts exert more pressure on firms to meet or beat analyst forecasts. In contrast, Bradley et al., 2022 find that analyst coverage is related to improved workplace safety, supporting analysts' monitoring role in improving ESG performance.

Ioannou and Serafeim (2015) find a shift in analysts' recommendations for firms with high ESG ratings from more pessimistic to more optimistic, and that experienced analysts are the first to shift. Their findings suggest that there is cross-sectional variation in analysts' attitudes towards ESG performance. To the extent that analysts with more ESG expertise have a better understanding of determinants of good ESG performance, they are in a better position to monitor the ESG-related strategies and activities of the firm. Thus, under the monitoring hypothesis, coverage by analysts with more ESG expertise is expected to increase firms' ESG performance. An alternative view, the pressure hypothesis, predicts that managers tend to cut long-term expenditures such as ESG expenditure when facing the pressure to meet analyst forecasts. However, it is unlikely that analysts with ESG expertise will create extra pressure on managers to meet financial goals than other analysts. Instead, firms covered by analysts with greater ESG expertise are likely to expect that these analysts will be monitoring ESG performance, and therefore, these firms may have incentives to limit these ESG expenditure cuts. A channel for analysts to express their opinions on ESG issues is through the earnings conference calls (Bochkay, Hales, & Serafeim, 2021). As an example, in the Q&A section of Altria Group's 2018 Q1 Earnings Call, Judy Hong, classified as an ESG expert analyst in our sample, asked questions on youth access to e-vapor tobacco products, illustrating ESG expert analysts' monitoring role in ESG issues. Taken together, these arguments predict that analysts' ESG expertise will be positively related to ESG performance.

In contrast, if ESG information is associated with ESG initiatives and activities with different payoffs across firms, knowledge acquired from ESG expertise with one firm may not spill over to other firms. In this case, analysts with greater ESG expertise would not necessarily be more effective monitors of ESG strategies and activities. Further, under the pressure hypothesis, if managers cut ESG expenditures to meet the short-term forecasts of analysts in general, ESG performance could decline. However, we expect that when firms are covered by analysts with greater ESG expertise, these analysts can mitigate short-term performance pressures by emphasizing the long-term benefits of ESG investments. Thus, we investigate a third hypothesis:

H3. *Analysts' ESG expertise is related to improved ESG performance.*

3.2. Research design and data

H3 examines the relationship between ESG expert analyst coverage and ESG performance. Most prior studies examine the relationship between firm characteristics and total analyst coverage and do not consider coverage by analysts with specific characteristics (Adhikari, 2016; He & Tian, 2013; Huang, Pereira, & Wang, 2017) except Yu (2008) and Bradley et al. (2017). Yu (2008) examines coverage by analysts with longer experience or from top brokers, and Bradley et al. (2017) examine coverage by analysts with pre-industry experience. Following these two studies, we estimate the following model:

$$ESGP_{jt+1} = \alpha + \beta_1\, Cover_{jt} \left[or\ \beta_2 ESG\ Expert\ Cover_{jt} + \beta_3 Non - ESG\ Expert\ Cover_{jt}\right] + \beta_4 Avg\ Gen\ Experience_{jt} + \beta_5 Avg\ Firm\ Experience_{jt} + \beta_6 Avg\ Port\ Size_{jt} + \beta_7 Avg\ NCIS_{jt} + \beta_8\ Avg\ Top10 + controls + \varepsilon \quad (6)$$

The dependent variable is ESG performance ($ESGP_{jt+1}$) measured by the most recent ESG ratings from Sustainalytics for firm j in year $t+1$. We first estimate the effect of total analyst coverage (*Cover*) on ESG performance. Next, we estimate the effect by decomposing total analyst coverage into ESG expert analyst coverage (*ESG Expert Cover*) and non-ESG expert analyst coverage (*Non-ESG Expert Cover*). $ESG\ Expert\ Cover_{jt}$ is defined as the number of ESG expert analysts following firm j in year t. Analyst i is defined as an ESG expert analyst if their industry ESG expertise is above the industry-year median. $Non\text{-}ESG\ Expert\ Cover_{jt}$ is total analyst coverage minus ESG expert analyst coverage. In addition to firm-level variables in eq. (3), we control for average analyst characteristics (*Avg Gen Exp*, *Avg Firm Exp*, *Avg Port Size*, *Avg Num SIC2, Avg Top10*) of all analysts following firm j at year t.

We retain observations with Sustainalytics or Bloomberg ratings in the subsequent year and exclude observations with missing variables in eq. (6). This provides a maximum sample of 7904 firm-years for analysis of analysts' monitoring role on ESG performance with a sample period from 2010 to 2017.[19]

3.3. Empirical results

3.3.1. Baseline models

H3 focuses on analysts' monitoring role and firms' ESG performance (*ESGP*). Table 1 Panel C reports summary statistics for variables included in the monitoring model. Table 6 presents the results of the effects of ESG expert analyst coverage on one-year-ahead *ESGP*.

Column (1) examines the effect of total analyst coverage on ESG performance. *Cover* is positively related to *ESGP*, indicating that firms covered by more analysts are more likely to improve their ESG performance. Next, we decompose total analyst coverage into ESG expert analysts (*ESG Expert Cover*) and non-ESG expert analysts (*Non-ESG Expert Cover*). Column (2) shows that the coefficient of *ESG Expert Cover* is positive and significant at the 1% level. Firms covered by 17 ESG expert analysts (75th percentile) have ESG ratings that are 1.57 points higher in the following year compared to firms covered by 3 ESG expert analysts (25th percentile). This increase represents a 2.93% rise relative to the mean ESG rating (mean = 53.38), suggesting a modest improvement at the aggregate level. However, when viewed relative to the interquartile range (IQR = 12), the 1.57-point increase accounts for a 13.08% rise, indicating a meaningful shift considering the relatively narrow variation in ESG scores across firms. In contrast, the coefficient of *Non-ESG Expert Cover* is not significant. The results suggest that ESG expert analysts play an effective monitoring role in improving firms'

[19] The sample period for the monitoring tests is six-month shorter than forecasting performance tests for two reasons. First, we calculate ESG expert coverage, the main variable of interest in monitoring tests based on the number of ESG expert analysts following firm j in year t. However, we only have six months of data for 2018 which results in a smaller analyst coverage number in 2018. Second, the Sustainalytics ratings are mostly issued in December. The rating methodology of Sustainalytics ratings changed significantly after September 2019, causing the new ratings to be not comparable to the old ratings. Therefore, to eliminate potential measurement issues, we drop 2018 sample in the monitoring tests.

Table 6
Regression of ESGP on ESG expert analyst coverage.

Variable	(1)	(2)	(3)
Cover	0.0666***		
	(2.89)		
ESG Expert Cover		0.1120***	
		(4.53)	
Non-ESG Expert Cover		0.0044	
		(0.18)	
ˆESG Expert Cover			0.0987**
			(2.46)
ˆNon-ESG Expert Cover			−0.0190
			(−0.22)
Avg Gen Exp	−0.0432	−0.0482	−0.0484
	(−0.78)	(−0.89)	(−1.16)
Avg Firm Exp	0.1037	0.0837	0.0670
	(1.19)	(0.98)	(0.82)
Avg Port Size	0.0738**	0.0805**	0.0796***
	(2.08)	(2.30)	(2.94)
Avg Num SIC2	−0.2456*	−0.2445*	−0.2448**
	(−1.71)	(−1.73)	(−2.28)
Avg Top10	0.1084	−0.0352	−0.0921
	(0.22)	(−0.07)	(−0.18)
Size	−0.2615	−0.2304	−0.2089
	(−1.23)	(−1.06)	(−1.45)
BP	−0.2774	−0.3047	−0.3064**
	(−1.20)	(−1.30)	(−2.10)
ROA	0.1544	0.1770	0.1606
	(0.39)	(0.44)	(0.29)
Loss	0.3378	0.3022	0.3068*
	(1.61)	(1.46)	(1.73)
Age	0.0172	0.0194	0.0188
	(0.23)	(0.29)	(0.42)
Ret	0.0767	0.0563	0.0361
	(0.57)	(0.42)	(0.25)
N	7904	7904	7904
R^2	0.892	0.893	0.892
Firm FE	Y	Y	Y
Year FE	Y	Y	Y

This table presents regression results for the effect of ESG expert analyst coverage on ESGP, i.e., eq. (6). The dependent variable is the ESG score in year *t* + 1. The variable of interest in column (1) is *Cover* defined as the number of analysts following firm j in year t. The variables of interest in column (2) are *ESG Expert Cover* and *Non-ESG Expert Cover*. *ESG Expert Cover* (*Non-ESG Expert Cover*) is defined as the number of ESG expert analysts (non-ESG expert analysts) following firm j in year t. Column (3) presents the second stage results of two-stage least-squares (2SLS) regressions using the instrumented ESG expert coverage (*ˆESG Expert Cover*) and instrumented non-ESG expert coverage (*ˆNon-ESG Expert Cover*). See Appendix A for variable definitions. Firm fixed effects and year fixed effects are included. Robust standard errors clustered at the firm level are used to compute *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

ESGP.

A concern is that the positive relation between ESG expert coverage and ESG performance is driven by firm characteristics that are related to both coverage and *ESGP*. For example, some brokerage houses may specialize in ESG-sensitive industries (e.g., renewables or utilities), and these brokers may have more analysts with ESG expertise at the same time when they tend to cover firms that experience improvements in ESG performance. To address the endogeneity concern, we construct residual analyst coverage measures following Yu (2008) and Bradley et al. (2017). *ESG Expert Cover (residual)* [*Non-ESG Expert Cover (residual)*] is defined as the residuals from regressing ESG expert coverage (non-ESG expert coverage) on six firm characteristics, i.e., firm size, book-to-price ratio, ROA, prior loss indicator, firm age, and prior stock returns, as well as year fixed effects. Thus, the residuals are not related to these firm-specific controls and year effect variables. The results (Appendix C.3. Column (1)) reveal that the coefficient of *ESG Expert Cover (residual)* remains positive and significant. In contrast, *Non-ESG Expert Cover (residual)* is not significant.

Another potential endogeneity concern is reversed causality because ESG expert analysts could intentionally choose to cover firms with high ESG performance. To mitigate this concern, we use a change model with the change in ESG performance from year *t* to year *t* + *1* as the dependent variable and the change in ESG expert coverage, along with other firm characteristics from year *t-1* to year *t*, as independent variables (Appendix C.3. Column (2)). The coefficient of change in ESG expert coverage is positive and significant, indicating that an increase in ESG expert coverage leads to an increase in ESG performance. In contrast, the coefficient of non-ESG expert coverage is not significant.

In addition, following Yu (2008) and He and Tian (2013), we use a 2SLS instrumental variable (IV) approach. The IVs for *ESG Expert Cover* and *Non-ESG Expert Cover* are brokerage adjusted ESG expert coverage and brokerage adjusted non-ESG expert coverage, which are calculated based on changes in brokerage house size measured by the number of analysts in I/B/E/S from broker *m*. The rationale is that brokerage houses constantly expand or downsize their research departments in response to internal factors such as revenue fluctuations, changes in business strategy, and cost considerations. These adjustments determine the number of analysts a broker employs and, consequently, the number of firms the broker can cover, but they are unlikely to be driven by the ESG performance of any specific firm covered. When a brokerage house hires more (fewer) analysts, its overall coverage universe expands (contracts), mechanically altering the number of ESG-expert analysts and non-ESG-expert analysts assigned to firms for reasons unrelated to firms' future ESG outcomes. Therefore, changes in ESG expert coverage (or non-ESG expert coverage) driven by the variation in brokerage house sizes are exogenous. The expected coverages are calculated as follows:

$$Broker\ Adj\ ESG\ Expert\ Cover_{mjt} = (BrokerSize_{mt}/BrokerSize_{m0}) \times ESG\ Expert\ Cover_{mj0} \quad (7)$$

$$Broker\ Adj\ Non-ESG\ Expert\ Cover_{mjt} = (BrokerSize_{mt}/BrokerSize_{m0}) \times Non-ESG\ Expert\ Cover_{mj0} \quad (8)$$

and

$$Broker\ Adj\ ESG\ Expert\ Cover_{jt} = \sum_{m=1}^{N} Broker\ Adj\ ESG\ Expert\ Cover_{mjt} \quad (9)$$

$$Broker\ Adj\ Non-ESG\ Expert\ Cover_{jt} = \sum_{m=1}^{N} Broker\ \ Adj\ Non-ESG\ \ Expert\ Cover_{mjt} \quad (10)$$

Broker Adj ESG Expert Cover$_{mjt}$ (*Broker Adj Non-ESG Expert Cover*$_{mjt}$) is the brokerage adjusted number of ESG expert analysts (non-ESG expert analysts) following firm *j* from broker *m* in year *t*. *BrokerSize*$_{mt}$ (*BrokerSize*$_{m0}$) is the number of analysts employed by broker *m* in year *t* (the benchmark year 0). *ESG Expert Cover*$_{mj0}$ (*Non-ESG Expert Cover*$_{mj0}$) is the number of ESG expert analysts (non-ESG expert analysts) covering firm *j* from broker *m* in year 0 (benchmark year). The number is usually 0 or 1 as brokerage houses seldom assign more than one analyst to follow a firm. To maximize the sample size, we set our benchmark year as 2014.[20]

Broker Adj ESG Expert Cover$_{jt}$ (*Broker Adj Non-ESG Expert Cover*$_{jt}$) captures the change in ESG expert (non-ESG expert) coverage relative to the benchmark year that is driven by the change in brokerage house size, and this change is not related to the ESG performance of the forecasted firm. In the first stage, we regress *ESG Expert Cover* (or *Non-ESG Expert Cover*) on *Broker Adj ESG Expert Cover, Broker Adj Non-ESG Cover*, and the other variables from eq. (6). In the second stage, we use the instrumented ESG expert coverage, *ˆESG Expert Cover*, and the

[20] Result remains similar when setting benchmark year to the first year in our sample (i.e., 2010).

instrumented non-ESG expert coverage, *ˆNon-ESG Expert Cover*, the fitted values from the two first-stage models, as variables of interest. We regress ESG performance (*ESGP*) on *ˆESG Expert Cover*, *ˆ Non-ESG Expert Cover*, and the other variables in eq. (6). Column (3) of Table 6 reports the second stage result of the 2SLS regression. The coefficient of *ˆESG Expert Cover* remains positively significant and has a similar magnitude as in Column (2). Also consistent with Column (2), the coefficient of *ˆ Non-ESG Expert Cover* is insignificant. The Kleibergen-Paap rk LM statistic equals 130.19 ($p < 0.001$), rejecting the null of under-identification. Weak-instrument tests also confirm strong identification: the Cragg-Donald F statistic is 100.48, and the Kleibergen-Paap Wald F statistic is 49.32, both of which exceed the Stock-Yogo critical value for a 10% maximal IV size (7.03). These statistics support the validity of the instruments.[21]

Our results differ from Adhikari (2016) and Qian et al. (2019) who find a negative relation between ESG performance and total analyst coverage. This inconsistency could be due to the difference in the sample period and the source of ESG ratings. First, analysts' attitudes towards ESG are evolving over time. Ioannou and Serafeim (2015) find that the relation between average analyst recommendation levels and ESG performance shifted from negative to positive from 1993 to 2007. Adhikari's (2016) sample period is from 2001 to 2011 while our sample period is from 2010 to 2017. Thus, our study is more likely to capture analysts' growing positive attitudes towards ESG performance. Second, Adhikari (2016) and Qian et al. (2019) measure ESG performance as the difference between the number of ESG strengths and the number of ESG concerns from KLD ratings, while we use Sustainalytics ratings. As pointed out before, the Sustainalytics ratings are now the most commonly used ratings by analysts.[22]

3.3.2. Exogenous shock from broker mergers/closures

In a similar spirit to Kelly and Ljungqvist (2012) and Hong and Kacperczyk (2009), we exploit analyst coverage loss caused by broker mergers and closures as an alternative way to address endogeneity concerns. The method is widely used by prior studies (Adhikari, 2016; He & Tian, 2013; Huang et al., 2017; Li & You, 2015).

To identify brokerage house mergers and closures, we begin by identifying the firm-years when (1) it is the last year that analyst *i* provided forecasts for firm *j* and (2) it is the last year that brokerage house *m* provided forecasts for firm *j*. There are two possible reasons for this situation. First, the brokerage house stopped coverage of firm *j* in year $t + 1$ due to mergers or closures. Second, the brokerage house stopped providing information to IBES in year $t + 1$. After removing observations without Sustainalytics ratings or those that cannot be linked to I/B/E/S recommendation files, we obtain 1477 analyst-firm-years (145 brokers).

As I/B/E/S recommendation files provide abbreviations of brokers and analyst names (last name and first name initial), we identify the brokerage houses using the following sources. First, we use BrokerCheck, a website maintained by the Financial Industry Regulatory Authority (FINRA), which contains the employment history of FINRA-registered security industry professionals. Second, we use LinkedIn, especially for non-US brokerage houses. Third, we use a list of All-America star analysts which contains star analysts and their brokerage houses. Fourth, we compare analyst-broker pairs from prior sources with I/B/E/S data to identify the brokerage houses.

With brokers identified, we then search whether the brokers have merged or closed. We first search BrokerCheck, which shows the current status of the broker. If it has been terminated, we check the year of termination. In addition, we search LinkedIn, Bloomberg, and other websites for more information. If the year of termination is the year or the year after the last year that a brokerage house appears in I/B/E/S, we consider the broker was omitted from I/B/E/S due to the broker's closures or mergers. In this way, we identify 43 cases of broker closures and mergers as listed in Appendix B. We identify termination of coverage by analysts associated with these brokers in the year after the closure or merger.

Next, we construct a sample of control firms as follows. First, consistent with Bradley et al. (2017), we require control firms to be in the same size (*Size*) and book-to-market (*BP*) quintiles in the same year. In addition, we require control firms to be in the same past return (*Ret*) and total coverage (*Cover*) quintiles. We further require that control firms (1) have ESG ratings in the year of and the year after the broker event and (2) do not experience analyst losses in the year of or the year before the broker event. Last, we retain the control firm with the total analyst coverage number closest to the treatment firms. The final sample consists of 322 pairs of firms, among which 263 firm-years lost ESG expert analyst coverage.[23]

Panel A of Table 7 reports the means of the main firm characteristics of the treatment and control firms. The differences are not significant between the two groups except for total analyst coverage (*Cover*). The treatment group has significantly larger analyst coverage. To test the effect of analyst coverage loss on firms' ESG performance, we estimate the following regression to control for the effect of coverage:

$$\Delta ESGP_{j(t0,t0+1)} = \alpha + \beta_1 \left(Lost\ ESG\ Expert_{jt0} \right) + \beta_2 Cover_{jt0} + \beta_3 ESG\ Expert\ Cover_{jt0} + \beta_4 LagESGP_{jt0} + controls + \varepsilon_{jt0} \quad (11)$$

or

$$\Delta ESGP_{j(t0,t0+1)} = \alpha + \beta_1 \left(Lost\ Non-ESG\ Expert_{jt0} \right) + \beta_2 Cover_{jt0} + \beta_3 Non-ESG\ Expert\ Cover_{jt0} + \beta_4 LagESGP_{jt0} + controls + \varepsilon_{jt0} \quad (12)$$

where $\Delta ESGP_{j(t0,t0+1)}$ is the difference in ESG performance between the year after the broker event and the year of the broker event. The year of the broker event is defined as the last year that analyst *i* and broker *m* cover firm *j* for treatment firms and the same year for corresponding control firms. The ESG performance of the year of the broker event is defined as the most recent Sustainalytics ratings in the event year. *Lost ESG Expert*$_{jt0}$ is an indicator variable that equals one for the treatment group.

[21] Hansen's J statistic is not applicable in our main specification because the number of excluded instruments equals the number of endogenous regressors. As an additional check, we estimate a specification in which only *ESG Expert Cover* is treated as endogenous; in this case, Hansen's J equals **0.05 ($p = 0.822$)**, failing to reject the null of valid overidentifying restrictions.

[22] In additional test (Appendix C.3. Column (4)), we measure ESG performance using KLD ratings. We find that the coefficient of total analyst coverage (instrumented) is negative but not significant, suggesting that both reasons explain the difference. On one hand, the insignificant coefficient in a later sample period suggests that analysts' attitude towards ESG are more positive over time. On the other hand, the different effects of analyst coverage on ESG performance measured by KLD and Sustainalytics suggest that different measures could lead to different results. One important difference between ESG performance measured by KLD and Sustainalytics is the weights of ESG issues. KLD ratings are a battery of identified ESG strengths and concerns. Prior studies commonly use the difference between the number of strengths and concerns as measurement of ESG performance (i.e., all ESG issues are equally weighted). However, the measure neglects the fact that some ESG issues are more important than the others to a specific firm. In contrast, Sustainalytics ratings are calculated based on key ESG issues, which puts more weight on material ESG issues. Therefore, our findings suggest that analysts' monitoring role are more focused on key ESG areas (as measured by Sustainalytics).

[23] The high proportion of ESG expert analyst loss is possibly due to that ESG expert analysts tend to cover firms with ESG performance ratings (discussed in section 4).

Table 7
Exogenous shock from brokerage mergers/closures on ESG performance.

Panel A: Mean of main firm characteristics between treatment and control groups

	Treatment	Control	Differences	*t*-statistic	*p*-value
Size	9.73	9.80	−0.08	−0.81	0.42
BP	0.43	0.43	−0.00	−0.12	0.91
Ret	0.15	0.18	−0.03	−1.04	0.30
Cover	28.64	26.51	2.12	2.78	0.01
ESGP	58.04	57.31	0.72	1.07	0.29

Panel B: Quasi-natural experiment based on brokerage mergers/closures

	Lost ESG expert analysts			Lost other analysts		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lost ESG Expert	**−0.4814***	**−1.7718*****	**−1.7504****			
	(−1.94)	**(−2.67)**	**(−2.58)**			
Lost ESG Expert×ESG Expert Cover		**0.0579****	**0.0599****			
		(2.17)	**(2.22)**			
Lost Non-ESG Expert				**0.0748**	**−0.4305**	**−0.4359**
				(0.12)	**(−0.39)**	**(−0.38)**
Lost Non-ESG Expert×Non-ESG Expert Cover					**0.0585**	**0.0521**
					(0.52)	**(0.45)**
ESG Expert Cover	0.0222	−0.0109	−0.0244			
	(0.66)	(−0.29)	(−0.63)			
Non-ESG Expert Cover				−0.0482	−0.0720	−0.0773
				(−0.71)	(−0.80)	(−0.87)
Cover	0.0232	0.0228	0.0277	0.0321	0.0319	0.0370
	(0.75)	(0.74)	(0.86)	(0.68)	(0.68)	(0.68)
LagESGP	−0.0635***	−0.0629***	−0.0748***	−0.0905**	−0.0878**	−0.1167**
	(−4.67)	(−4.65)	(−5.13)	(−2.33)	(−2.21)	(−2.06)
Size			0.1545			−0.0513
			(1.16)			(−0.17)
BP			0.1651			0.7450
			(0.46)			(0.67)
ROA			0.3392			1.0451
			(0.26)			(0.24)
Ret			0.0177			−0.3040
			(0.04)			(−0.52)
Firm Age			0.0107			0.0298
			(1.34)			(1.18)
Constant	3.4157***	4.0930***	2.9442**	6.0474**	6.0622**	6.7983**
	(4.03)	(4.75)	(2.17)	(2.50)	(2.47)	(2.35)
N	526	526	526	118	118	118
R^2	0.091	0.099	0.107	0.422	0.424	0.440
Year FE	Y	Y	Y	Y	Y	Y

This table presents results of a quasi-natural experiment based on analyst coverage lost due to brokerage mergers and closures on ESGP. Panel A reports the mean of main firm characteristics between treatment and control groups. Panel B reports the regressions of lost ESG expert analysts (Columns 1–3) or lost other analysts (Columns 4–6). The dependent variable is ESGP score change from year *t* to year *t* + 1. *Lost ESG Exp* (*Lost NonESG Exp*) is an indicator variable that equals one if a ESG expert analyst (non-ESG expert analyst) stops coverage for firm *j* in year *t* due to brokerage mergers/closures (i.e., treatment group), and zero otherwise. See Appendix A for variable definitions. Year fixed effects are included. Robust standard errors clustered at the firm level are used to compute *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel B of Table 7 presents the regression results. The coefficient of *Lost ESG Expert* is negative and significant in column (1), indicating that loss of ESG expert coverage is related to decreased ESG performance in the following year. In contrast, the loss of other analyst coverage (i.e., a non-ESG expert) is not related to any significant change in ESG performance in column (4). We further examine whether the impact of ESG expert analyst loss varies with existing ESG expert analyst coverage. Columns (2) and (3) show that the interaction term between *Lost ESG Expert* and *ESG Expert Coverage* is positive and significant, indicating that the negative effects of ESG expert coverage loss on ESG performance are attenuated by greater ESG expert coverage. For the loss of other analyst coverage, columns (5) and (6) do not show any significant moderating effects of the existing coverage. Overall, the results provide further support for the monitoring role of ESG expert analysts on firms' ESG performance.

3.3.3. Additional analyses

In this subsection, we conduct additional analyses to evaluate the robustness and generalizability of our findings.

First, we consider individual components in ESG performance when estimating eq. (6). Table 8 reports the effects of ESG expert coverage on the environmental (*E*), social (*S*), and governance (*G*) aspects of ESG performance in columns (1) to (3), respectively. The coefficient of *ESG Expert Cover* is positive and significant in columns (1) and (2), indicating that ESG expert coverage is related to improved environmental and social performance. However, coverage by ESG experts is not related to better governance performance.

Next, we consider alternative measures for ESG expert coverage and report results in Table 9. First, as we classify an analyst as an ESG expert analyst based on industry ESG expertise in the baseline model, all non-ESG expert analysts have relatively low industry ESG expertise. However, some of these could have high non-industry ESG expertise, while others may have lower non-industry ESG expertise. Consequently, we

Table 8
Regression of ESG expert coverage on E/S/G performance.

Variable	(1) Environmental performance	(2) Social performance	(3) Governance performance
ESG Expert Cover	**0.1676*** (4.33)**	**0.1098*** (3.05)**	**0.0484 (1.53)**
Non-ESG Expert Cover	0.0093 (0.24)	−0.0298 (−0.83)	0.0200 (0.61)
Avg Gen Exp	−0.0603 (−0.53)	−0.0563 (−0.59)	−0.1579* (−1.88)
Avg Firm Exp	0.0215 (0.13)	0.3084** (2.26)	0.1191 (0.96)
Avg Port Size	0.1576** (2.18)	0.0423 (0.74)	0.1496*** (2.85)
Avg Num SIC2	−0.3079 (−1.10)	−0.2868 (−1.17)	−0.4266* (−1.81)
Avg Top10	0.0564 (0.05)	0.7726 (0.76)	−1.5822* (−1.69)
Size	−0.0265 (−0.09)	−0.2681 (−0.98)	−0.5720* (−1.93)
BP	−0.5941 (−1.36)	−0.5424 (−1.33)	−0.1168 (−0.41)
ROA	−1.6201 (−1.33)	0.1309 (0.12)	0.4985 (0.54)
LOSS	0.2789 (0.71)	0.7233** (2.03)	−0.2308 (−0.73)
Age	0.0139 (0.12)	0.1434 (1.48)	−0.0502* (−1.71)
Ret	−0.1268 (−0.44)	0.3086 (1.24)	0.0329 (0.14)
N	5714	5714	5714
R^2	0.867	0.809	0.803
Firm FE	Y	Y	Y
Year FE	Y	Y	Y

This table presents regression results for the effect of ESG expert analyst coverage on environmental (E), social (S), and governance (G) aspects of ESGP. The dependent variables are ESGP scores on E, S, and G aspects in year $t + 1$, respectively. See Appendix A for variable definitions. Firm fixed effects and year fixed effects are included. Robust standard errors clustered at the firm level are used to compute *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

split *Non-ESG Expert Cover* into two measures: *Non-ESG Expert Cover (H)* for coverage by non-ESG analysts with high non-industry ESG expertise and *Non-ESG Expert Cover (L)* for coverage by non-ESG analysts with low non-industry ESG expertise. In column (1), we find that the coefficient of *Non-ESG Expert Cover (H)* is positive and not significant, and that the coefficient of *Non-ESG Expert (L)* is negative and not significant. The former result indicates that greater coverage by analysts who gain ESG expertise in general industries, but do not have industry ESG expertise, is not associated with better ESG performance, consistent with the forecasting performance models that highlight the importance of ESG expertise from the same industry.

Second, we use the percentage of ESG expert analysts as an alternative proxy for the ESG expertise of the analysts following the firm. The positive coefficient of *ESG Expert%* in column (2) indicates that firms covered by a higher percentage of ESG expert analysts are more likely to have improved ESG performance in the following year. Third, we use ESG expertise measured by ASSET4 ratings to identify ESG experts. The coefficient of *ESG Expert Cover (ASSET4)* is significantly positive in column (3), indicating that ESG expert coverage based on ASSET4 data is also associated with higher ESG performance.

Table 9
Alternative regressions of ESGP on ESG expert analyst coverage.

Variable	(1)	(2)	(3)
ESG Expert Cover	**0.1170*** (4.63)**		
Non-ESG Expert Cover (H)	0.0372 (1.03)		
Non-ESG Expert Cover (L)	−0.0177 (−0.65)		
ESG Expert%		**0.6947* (1.90)**	
Cover		0.0669*** (2.90)	
ESG Expert Cover (ASSET4)			**0.1446*** (3.21)**
Non-ESG Expert Cover (ASSET4)			0.0162 (0.35)
Avg Gen Exp	−0.0468 (−0.86)	−0.0452 (−0.82)	−0.2674*** (−3.27)
Avg Firm Exp	0.0862 (1.00)	0.0983 (1.13)	0.5885*** (4.60)
Avg Port Size	0.0840** (2.40)	0.0738** (2.10)	0.1690*** (3.11)
Avg Num SIC2	−0.2491* (−1.76)	−0.2319 (−1.62)	−0.5946** (−2.33)
Avg Top10	−0.0373 (−0.08)	0.0427 (0.09)	−0.6818 (−0.77)
Size	−0.2160 (−1.01)	−0.2592 (−1.20)	1.0890*** (3.14)
BP	−0.3042 (−1.30)	−0.2807 (−1.21)	0.3335 (1.08)
ROA	0.1510 (0.38)	0.1263 (0.32)	0.7365 (0.79)
LOSS	0.2981 (1.45)	0.3372 (1.61)	0.0154 (0.05)
Age	0.0195 (0.30)	0.0176 (0.24)	0.1045*** (3.03)
Ret	0.0551 (0.41)	0.0784 (0.58)	−0.5733*** (−2.66)
Constant	−0.0468 (−0.86)	−0.0452 (−0.82)	−0.2674*** (−3.27)
N	7904	7904	9344
R^2	0.893	0.892	0.910
Firm FE	Y	Y	Y
Year FE	Y	Y	Y

This table presents alternative regressions for the effect of ESG expert analyst coverage on ESGP. The dependent variable is Sustainalytics scores for ESGP in year $t + 1$ for Columns (1) and (2) and ASSET4 scores for Column (3). Column (1) splits *Non-ESG Expert Cover* into two parts. *Non-ESG Expert Cover (H)* [*Non-ESG Expert Cover (L)*] is coverage by non-ESG analysts with non-industry ESG expertise that is higher than the medians. Column (2) uses *ESG Expert%*, in place of *ESG Expert Cover*. Column (3) uses ESG expert analyst coverage measured by experience with firms with ASSET4 ESG ratings [*ESG Expert Cover (Asset4)*] in place of *ESG Expert Cover*. See Appendix A for variable definitions. Firm fixed effects and year fixed effects are included. Robust standard errors clustered at the firm level are used to compute *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Last, to explore possible thresholds for ESG expert analysts, we split analysts into quartiles based on their industry ESG expertise. The results (Appendix C.3. Column (3)) indicate that the influence of ESG expert coverage is most pronounced for analysts in the top quartile (Q4), followed by the third quartile, while no significant effects are observed for analysts in the bottom two quartiles. This indicates that analysts with greater-than-median ESG expertise are more effective in monitoring firms' ESG performance.

Table 10
The effects of coverage initiation by third-party ESG ratings provider on ESG expert coverage.

	(1)	(2)	(3)
Variable	Sustainalytics	ASSET4	Bloomberg
Treat (SA)	**2.9122*** **		
	(15.35)		
Treat (ASSET4)		**1.1201*** **	
		(8.22)	
Treat (Bloomberg)			**1.9659*** **
			(8.32)
Size	0.3346***	0.0751	0.8774***
	(4.38)	(1.44)	(7.77)
BP	0.5842**	0.1755	0.2555
	(2.30)	(0.76)	(0.92)
ROA	0.0585	−0.1094	−2.3139**
	(1.25)	(−0.41)	(−2.33)
Loss	0.4800**	0.4551**	−0.5623
	(2.01)	(2.45)	(−1.32)
Firm Age	0.0083	−0.0147**	0.0106
	(1.06)	(−2.54)	(1.14)
Past Ret	0.3922**	0.4180***	0.2968
	(2.09)	(3.01)	(1.12)
Constant	−2.3127***	−0.5932	−5.0331***
	(−3.81)	(−1.45)	(−5.91)
N	2514	1703	2054
R^2	0.361	0.179	0.387
Industry FE	Y	Y	Y
Year FE	Y	Y	Y

This table presents regressions for the effect of coverage initiation by third-party ESG rating providers on ESG expert coverage. The dependent variable is the change of ESG expert analyst coverage from year t-1 to year $t + 1$. The sample consists of firm-years with ESG rating coverage initiation and propensity-score matched sample. *Treat* is an indicator variable that equals one if the third-party ESG rating provider initiates coverage for firm j in year t (i.e., treatment group), zero otherwise. See Appendix A for variable definitions. Robust standard errors clustered at the firm level are used to compute t-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

4. Part III: ESG expertise and coverage decision

As a final analysis, we examine the effects of the initiation of third-party ESG rating coverage on coverage by ESG expert analysts. We retain all firm-years where an ESG rating by Sustainalytics, ASSET4, or Bloomberg was issued for the first time. To isolate the effect of ESG rating initiation, we compare the initiation sample against a control sample with similar firm characteristics but not covered by specific ESG ratings. We use propensity score matching (PSM) to construct the control sample which mitigates selection bias by controlling for the observable determinants of ESG rating initiations. For each firm-year with an ESG rating initiation, we select control firms from the same year with a propensity score closest to the initiation firm. The matching is done without replacement and with a maximum distance (i.e., a calliper) of 0.01. To calculate the propensity score, we estimate a first-stage model where the probability of ESG rating initiation by Sustainalytics, ASSET4, or Bloomberg is a function of firm size, book-to-market ratio, ROA, a loss indicator, firm age, prior stock returns, and industry fixed effects. In the second stage, we regress the change in ESG expert coverage on a treatment indicator (*Treat*), firm controls, and industry and year fixed effects.

Table 10 shows that the coefficients of *Treat* in all three columns are positive, indicating that compared with control firms, firms experience a greater increase in ESG expert coverage after the initiation of coverage by Sustainalytics, ASSET4, or Bloomberg. Collectively, the results show that ESG expert analysts tend to cover firms when more ESG information becomes publicly available.

5. Conclusion

In capital markets, financial analysts process complex information and translate it into earnings forecasts, forecast revisions, and monitoring activities. Despite evidence that ESG disclosure is related to improved analysts' forecast accuracy (Bernardi & Stark, 2018; Dhaliwal et al., 2011; Dhaliwal et al., 2012), an open question is whether analysts differ in their ability to process ESG-related information. This paper attempts to fill this gap.

We tackle this question by examining whether expertise gained from analyzing ESG information increases their forecasting ability and monitoring effectiveness. As third-party ESG ratings are widely used by investors, we measure analysts' ESG expertise using the cumulative number of firms with ESG ratings by Sustainalytics that an analyst followed in the past five years. A distinctive contribution of our study is to separate this expertise into industry-specific and non-industry ESG expertise, which allows us to identify heterogeneity in ESG expertise. We focus on an analyst's industry ESG expertise which is their ESG expertise from covering firms in the same industry as the forecasted firm.

We find that analysts with industry ESG expertise issue more accurate forecasts. We also find that market reaction is more pronounced for upward revisions issued by analysts with greater industry ESG expertise, especially for firms with ESG ratings. In contrast, non-industry ESG expertise does not provide the same benefits and can even reduce accuracy. Thus, we contribute to the existing analyst literature by identifying a new type of analyst expertise that is associated with forecasting performance. Moreover, the results imply that not all analysts are equally capable of analyzing ESG information and highlight the importance of industry-relevant ESG knowledge in analysts' information-intermediary role.

For the external monitoring role, we find that coverage by more industry ESG expert analysts improves firms' ESG performance, but not for coverage from analysts with more non-industry expertise. The causal effect is robust to the tests of endogeneity, including instrumental variables and exogenous shocks from broker mergers and closures. Finally, we examine whether ESG ratings affects analysts' coverage decisions. We document that ESG expert analysts tend to follow firms with ESG ratings. Again, the results highlight the different attitudes towards ESG information for analysts with different levels of ESG expertise, suggesting that ESG expert analysts recognize their advantage in processing and incorporating ESG information.

To be noted, our interpretation is that the superior forecast performance of ESG expert analysts is primarily driven by task-specific experience in processing and interpreting ESG information, consistent with prior evidence that specialized experience improves analysts' information processing and forecast quality (Clement et al., 2007; Hilary & Shen, 2013). However, our empirical design does not allow us to directly observe analysts' private information, and we therefore cannot fully rule out the possibility that some analysts also benefit from information advantages. Although the Regulation Fair Disclosure adopted in 2000 restricts selective disclosure of material information, this distinction cannot be cleanly identified in our setting. We acknowledge this limitation and leave disentangling information-processing advantages from private-information channels for future research.

Overall, our findings highlight the importance of domain-specific non-financial expertise in shaping analysts' forecasting performance, monitoring effectiveness, and coverage decisions. By documenting that the industry relevance of ESG expertise is crucial, our study contributes to the literature on analyst specialization and information processing.

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Appendix A. Appendix

Variable Definitions

Variable	Definition
ESG expertise	
Ind ESG Exp	*Ind ESG Exp* is calculated as the residual from: Industry ESG exposure$_{ijt}$ = α + β_1Industry coverage$_{ijt}$ + β_2General coverage$_{ijt}$ + ε_{ijt} (1) where 'related' indicates experience associated with firms in the same two-digit SIC industry as the forecasted firm.
Non-ind ESG Exp	*Non-ind ESG Exp* is calculated as the residual from: Non-industry ESG exposure$_{ijt}$ = α + β_1Industry coverage$_{ijt}$ + β_2General coverage$_{ijt}$ + ε_{ijt} (2) where 'general' indicates experience associated with firms not in the same two-digit SIC industry as the forecasted firm.
ESG expert analyst coverage	
ESG Expert Cover	Number of analysts with higher than median *Ind ESG Exp* following firm *j* at time *t*.
Cover	Number of analysts following firm *j* at time *t*.
Non-ESG Expert Cover	Number of non-ESG expert analysts following firm *j* at time *t* (i.e., *Cover* minus *ESG Expert Cover*).
ESG Expert%	ESG expert analyst coverage divided by total analyst coverage.
Lost ESG Expert	Indicator variable equals one if a firm loses ESG expert analyst coverage due to broker closure or merger in the current year, zero otherwise.
Lost Non-ESG Expert	Indicator variable equals to one if a firm loses non-ESG expert analyst coverage due to broker closure or merger in the current year, zero otherwise.
Treat (SA)	Indicator variable equals to one if Sustainalytics initiates coverage for firm *j* in year *t*, zero otherwise.
Treat (ASSET4)	Indicator variable is one if ASSET4 initiates coverage for firm *j* in year, zero otherwise.
Treat (Bloomberg)	Indicator variable equals to one if Bloomberg initiates coverage for firm *j* in year *t*, zero otherwise.
Other variables	
PMAFE	Proportional mean-adjusted absolute forecast error, $PMAFE_{ijt} = (AFE_{ijt} - MAFE_{jt})/MAFE_{jt}$ AFE_{ijt} = Abs(Forecast EPS$_{ijt}$ – Actual EPS$_{ijt}$) 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*.
CAR	DGTW adjusted return, i.e., cumulative abnormal returns calculated following Daniel et al. (1997) over the three-trading-day window.
BHAR	Buy-and-hold DGTW adjusted return over [−1,+62] trading day window.
Gen Exp	Mean-adjusted general expertise where general expertise is defined as the number of years since analyst *i* issued the first annual earnings forecast in I/B/E/S.
Firm Exp	Mean-adjusted firm-specific experience where firm-specific experience is defined as the number of years since analyst *i* issued the first annual earnings forecast for firm *j* in I/B/E/S.
Horizon	Mean-adjusted forecast age where age is the number of days from the forecast date to 30 days prior to the fiscal period end.
Port Size	Mean-adjusted portfolio size where portfolio size is the number of firms followed by analyst *i* at time *t*.
Num SIC2	Mean-adjusted number of SIC industries followed by analyst *i* at time *t*.
Top 10	Mean-adjusted dummy variable with the value of one if analyst *i* works at a top decile broker (in terms of the number of analysts) at time *t*, zero otherwise.
Size	Natural log of the market capitalization of firm *j* (in million $) at time *t*.
BP	Book-to-market ratio
ROA	Return on asset ratio
Loss	Indicator variable with the value of one if firm *j* reports loss at time *t*, zero otherwise.
Age	Firm age
Ret	Past 12-month stock returns
Revision	Forecast revision following Ivković and Jegadeesh (2004). Revision is defined as the difference between analyst *i*'s forecast for firm *j* for year *t* at time *k* and the previous forecast at time *k*-1 scaled by the absolute value forecast at time *k*-1. The denominator is set to 0.01 if lower. Values are multiplied by 100 and are truncated between −50% and 50%.
LagPMAFE	Lagged *PMAFE* defined as *PMAFE* of the most recent forecast issued by analyst *i* for firm *j* for year *t*-1.
ESGP	ESG performance. Sustainalytics ratings for firm *j* in December year *t*.
Avg Gen Exp	Mean of general experience for all analysts following firm *j* in year *t*.
Avg Firm Exp	Mean of firm-specific experience for all analysts following firm *j* in year *t*.
Avg Port Size	Mean of portfolio size for all analysts following firm *j* in year *t*.
Avg Num SIC2	Mean of the number of two-digit SIC industries followed for all analysts following firm *j* in year *t*.
Avg Top10	Percentage of analysts following firm *j* in year *t* that are from top 10% brokers.

Appendix B

List of brokerage house mergers and closures.

ESTIMID	Company Name	Status
POORSTAN	Monroe Wealth Management, LLC	Terminated in 2015
STERNE	Sterne, Agee & Leach, Inc.	Terminated in 2017
MKEEGAN	Morgan Keegan & Company, LLC	Linkedin: From 2 April 2012, Morgan Keegan & Company, LLC operates as a subsidiary of Raymond James Financial, Inc.
FGS	FGS Capital LLP	Dissolved in 2017
AMERTECH	American Technology Research, Inc.	Terminated in 2010
GLOCROWN	Global Crown Capital, LLC	Expelled in 2009
CRTCAP	CRT Capital Group LLC	Terminated in 2016

(*continued on next page*)

Appendix B (*continued*)

ESTIMID	Company Name	Status
BRIGANUS	Brigantine Advisors LLC	Merged in 2012
PRITCHAR	Pritchard Capital Partners, LLC	Expelled in 2012
DAHLROSE	Dahlman Rose & Co.	Terminated in 2013
TOPEKA	Topeka Capital Markets Inc.	Terminated in 2016
GILFORD	Gilford Securities Incorporated	Terminated in 2015
BURKE	Burke & Quick Partners LLC	Terminated in 2018
BGBSEC	BGB Securities, Inc.	Terminated in 2013
GHUNTER	Global Hunter Securities, LLC	Terminated in 2015
HOWEBARN	Howe Barnes Hoefer & Arnett, Inc	Terminated in 2013
HALLUM	ThinkEquity LLC	Terminated in 2013
WEISEL	Thomas Weisel Partners LLC	Terminated in 2012
MABON	Rodman & Renshaw, LLC	Terminated in 2012
PORTALES	Portales Partners, LLC	Terminated in 2016
THEJUDAG	The Juda Group	Co-founder left, LinkedIn, 2015
SRIDGE	Southridge Investment Group LLC	Terminated in 2011
CARISCO	Caris & Co., Inc	Terminated in 2013
TICON	Ticonderoga Securities LLC	Terminated in 2012
JESUPLAM	Jesup & Lamont Securities Corp	Expelled in 2010
CRAIG	Craig-Hallum Capital Group, Inc	Terminated in 2013
CROWELL	Crowell, Weedon & Co.	Terminated in 2014
MILLERTA	Miller Tabak + Co., LLC	Terminated in 2014
ZACHARY	Zachary Investment Research & Management, LLC	Terminated in 2013
UNTERBUR	Collins Stewart, Inc	Terminated in 2012
FULGLO	Soleil Securities Corporation	Terminated in 2011
TORMARES	Torma Research	Terminated in 2011
MCADAMS	McAdams Wright Ragen, Inc.	Terminated in 2015
SOLEILT	Soleil (Tenner Investment Research)	Terminated in 2011
DUDACK	Dudack Research Group	Terminated in 2011
NEXTGENE	Next Generation Equity Research	Terminated in 2010
HMGLOBAL	HM Global Capital LLC, Research Division	Terminated in 2014
SIMMONS	Simmons & Co. International	Terminated in 2016
ATHLOS	Athlos Research, LLC	Terminated in 2016
ORION	Orion Trading, LLC	Cancelled in 2017
AVIAN	Avian Securities, LLC	Terminated in 2013
MIDEST	FTN Equity Capital Markets Corp.	Terminated in 2010
PPARTGRP	Phoenix Derivatives Group, LLC	Terminated in 2013

Appendix C.1
ESG rating coverage and forecast accuracy.

	(1)	(2)	(3)
Variables	Sustainalytics	ASSET4	Bloomberg
Ind ESG Exp×Has Rating	**−0.0031*****	**−0.0025*****	**−0.0031*****
	(−4.78)	**(−3.56)**	**(−5.37)**
Ind ESG Exp	−0.0023**	−0.0024***	−0.0027***
	(−2.53)	(−2.77)	(−3.74)
Non-ind ESG Exp×Has Rating	0.0014***	0.0003	0.0014**
	(2.86)	(0.55)	(2.54)
Non-ind ESG Exp	0.0015***	0.0022***	0.0018***
	(3.55)	(4.56)	(4.48)
Has Rating	−0.0386***	−0.0235***	0.0066
	(−9.71)	(−4.72)	(1.36)
Gen Exp	−0.0014	−0.0015	−0.0015
	(−1.22)	(−1.26)	(−1.31)
Firm Exp	−0.0061***	−0.0063***	−0.0066***
	(−3.75)	(−3.88)	(−4.00)
Horizon	0.0032***	0.0032***	0.0032***
	(93.92)	(93.84)	(93.87)
Port Size	−0.0008	−0.0008	−0.0008
	(−1.48)	(−1.49)	(−1.46)
Num SIC2	0.0051***	0.0051***	0.0050**
	(2.59)	(2.61)	(2.51)
Top 10	0.0026	0.0027	0.0030
	(0.38)	(0.39)	(0.44)
Cover	−0.0010*	−0.0010*	−0.0011**
	(−1.87)	(−1.85)	(−2.01)
Size	−0.0015	−0.0012	−0.0020
	(−0.39)	(−0.31)	(−0.53)
BP	−0.0136***	−0.0135***	−0.0138***
	(−4.52)	(−4.50)	(−4.52)
ROA	0.0019**	0.0019**	0.0019**

(*continued on next page*)

Appendix C.1 (*continued*)

	(1)	(2)	(3)
Variables	Sustainalytics	ASSET4	Bloomberg
	(2.39)	(2.39)	(2.34)
Loss	0.0061	0.0063	0.0065
	(1.17)	(1.21)	(1.25)
Age	−0.0000	−0.0006	−0.0011
	(−0.04)	(−0.73)	(−1.27)
Ret	0.0064*	0.0064*	0.0066*
	(1.84)	(1.82)	(1.88)
Constant	0.0445	0.0500	0.0563
	(1.19)	(1.33)	(1.43)
N	1,242,958	1,242,958	1,242,958
R^2	0.282	0.281	0.281
Analyst-firm FE	Y	Y	Y

This table presents the moderating effect of ESG rating coverage on relationship between analysts' forecast accuracy and industry ESG expertise, i.e., eq. (3). The dependent variable is the proportional mean absolute forecast error (*PMAFE*). Industry ESG expertise [*Ind ESG Exp*] is derived from eqs. (1) and (2). *Has Rating* is a dummy variable which equals to one if the firm is covered by Sustainalytics (ASSET4, Bloomberg) in Column (1) [or (2), (3)]. See Appendix A for variable definitions. Analyst-firm fixed effects are included to control for analysts' innate ability. Robust standard errors double-clustered at the firm and analyst levels are used to compute the *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Appendix C.2

Robustness tests for ESG expertise and market reaction to forecast revisions.

Panel A: Upward Earnings Forecast Revisions

Variables	(1)	(2)	(3)	(4)
Revision*×*Ind ESG Exp	**0.0033***	**0.0026*****	**0.0023****	**0.0018*****
	(1.93)	**(2.70)**	**(2.40)**	**(2.79)**
Ind ESG Exp	−0.0450**	−0.0091	−0.0022	−0.0091
	(−2.18)	(−0.76)	(−0.18)	(−1.06)
Revision×*Non-ind ESG Exp*	0.0011	−0.0005	−0.0005	−0.0000
	(0.74)	(−0.44)	(−0.47)	(−0.02)
Non-ind ESG Exp	0.0049	0.0197**	0.0182*	0.0121*
	(0.31)	(2.09)	(1.84)	(1.67)
Revision	0.0788***	0.0441***	0.0317**	0.0373***
	(5.31)	(3.05)	(2.43)	(3.04)
N	125,344	301,076	301,348	367,326
R^2	0.042	0.036	0.037	0.032
Constant	Y	Y	Y	Y
Analyst Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Panel B: Downward Earnings Forecast Revisions

Variables	(1)	(2)	(3)	(4)
Revision*×*Ind ESG Exp	**−0.0027**	**−0.0030*****	**−0.0026*****	**−0.0014***
	(−1.56)	**(−3.16)**	**(−2.62)**	**(−1.85)**
Ind ESG Exp	−0.0114	−0.0235*	−0.0164	−0.0199**
	(−0.55)	(−1.72)	(−1.15)	(−2.03)
Revision×*Non-ind ESG Exp*	−0.0021	−0.0016	−0.0013	0.0004
	(−1.33)	(−1.50)	(−1.26)	(0.56)
Non-ind ESG Exp	−0.0288	−0.0191	−0.0273**	−0.0035
	(−1.45)	(−1.54)	(−2.11)	(−0.38)
Revision	0.0626***	0.0438***	0.0253*	0.0337***
	(4.22)	(3.45)	(1.94)	(2.84)
N	145,149	308,769	295,595	364,473
R^2	0.034	0.029	0.029	0.026
Constant	Y	Y	Y	Y
Analyst Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

This table presents the robustness tests for regression analysis of market reactions to earnings forecast revisions on industry ESG expertise, i.e., eq. (5). The dependent variable is the cumulative abnormal return over the three-trading-day window around the forecast announcement (i.e., CAR[−1,+1]). The variable of interest is the interaction term of revision and industry ESG expertise (*Revision*×*Related ESG Exp*). Panel A presents the results for upward revisions (i.e., the forecast which is higher than the analyst's previous forecast for the same firm for the same year). Panel B presents the results for downward revisions. Column (1) restricts the sample to forecasts that are the only forecast for firm *j* at date *k*. Column (2) excludes analysts with no ESG expertise. Column (3) restricts the sample to analysts with no less than five years of general

experience. Column (4) uses ESG expertise measured by ASSET4 ratings. See Appendix A for variable definitions. Firm fixed effects and year fixed effects are included. Robust standard errors doubled-clustered at the firm and analyst levels are used to compute *t*-statistics in parentheses. All coefficients are multiplied by 1000. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Appendix C.3
Robustness tests for ESGP and ESG expert analyst coverage.

Variable	(1)	(2)	(3)	(4)
ESG Expert Cover (Residual)	**0.0978*** **			
	(4.23)			
Non-ESG Expert Cover (Residual)	−0.0167			
	(−0.63)			
ESG Expert Cover (Change)		**0.0513** **		
		(2.43)		
Non-ESG Expert Cover (Change)		−0.0028		
		(−0.11)		
Cover ESG Exp Q4			**0.1376*** **	
			(5.47)	
Cover ESG Exp Q3			**0.0526***	
			(1.76)	
Cover ESG Exp Q2			−0.0442	
			(−1.45)	
Cover ESG Exp Q1			0.0209	
			(0.68)	
^ESG Expert Cover				**0.0001**
				(0.09)
^Non-ESG Expert Cover				0.0026
				(1.27)
N	7904	5462	7904	14,698
R^2	0.893	0.261	0.894	0.627
Constant	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

This table presents robustness tests for regression for the effect of ESG expert analyst coverage on ESGP, i.e., eq. (6). For Column (1), the dependent variable is the Sutainalytics ESG score in year $t + 1$. *ESG Expert Cover (residual)* [*Non-ESG Expert Cover (residual)*] is defined as the residuals from regressing ESG expert coverage (non-ESG expert coverage) on six firm characteristics, i.e., firm size, book-to-price ratio, ROA, prior loss indicator, firm age, and prior stock returns, as well as year fixed effects. For Column (2), the dependent variable is the difference of Sutainalytics ESG score in year $t + 1$ and year t. The independent variable *ESG Expert Cover (change)* [*Non-ESG Expert Cover (change)*] is defined as the difference between the variable in year t and year t-*1*. The control variables are defined as change forms similarly. For Column (3), the dependent variable is the Sutainalytics ESG score in year $t + 1$. *Cover ESG Exp Q4* (3, 2, and 1) is defined as the number of analysts with top (Q3, Q2, or bottom) quartile *Ind ESG Exp* following firm *j* in year *t*. Column (4) presents the second stage results of two-stage least-squares (2SLS) regressions using the instrumented ESG expert coverage (*^ESG Expert Cover*) and instrumented non-ESG expert coverage (*^Non-ESG Expert Cover*) using KLD ESG rating in year $t + 1$ as dependent variable. Firm fixed effects and year fixed effects are included. Robust standard errors clustered at the firm level are used to compute *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Data availability

Data will be made available on request.

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