The Anti-ESG Movement and Analyst Responses to ESG Information: The Emergence of ESG Clienteles*

Jing-Chi (George) Chen
University of West Georgia
jchen@westga.edu

Devin Shanthikumar†
University of California Irvine
dshanthi@uci.edu

Sijing Wei
Creighton University
sijingwei@creighton.edu

Jiarui (Iris) Zhang
California State University-Long Beach
iris.zhang@csulb.edu

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† Corresponding author.

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Abstract

We study how the anti-ESG movement affects analysts' use of ESG information, exploiting staggered state-level anti-ESG legislation. The ESG coverage premium for ESG-reporting firms declines in anti-ESG states, driven by non-ESG-oriented analysts, while ESG-oriented analysts maintain coverage. Cross-group earnings forecast dispersion rises, indicating increasing differences of opinion. Further, non-ESG-oriented analysts' forecast accuracy decreases for ESG-reporting firms. Anti-ESG-related cross-group dispersion is associated with higher concurrent abnormal trading volume, spreads, and idiosyncratic volatility, and higher volume and spreads around subsequent earnings announcements. Together, our results indicate that analyst coverage of ESG-reporting firms reflects diverging ESG clienteles in the anti-ESG era.

I. Introduction

The growing anti-ESG movement raises fundamental questions about investors' interest in Environmental, Social, and Governance (ESG), and analysts' responses. In this study, we examine how analyst coverage and earnings forecasts for ESG-reporting firms respond to anti-ESG sentiment. There is growing recognition that investors differ in their preferences for ESG performance. Starks (2023) frames ESG-related investing as being primarily driven by the perceived *value* of ESG investments, such as reducing or managing exposure to ESG-related risk, and/or investor *values*, their non-pecuniary preferences for firms' environmental, social, or governance choices. Friedman, Heinle, and Luneva (2021) distinguish between "cash flow-minded" investors and "ESG-minded" investors. Goldstein, Kopytov, Shen, and Xiang (2024) model "green" (ESG-oriented) and "traditional" (non-ESG-oriented) investors who differ in how they weight or interpret financial versus ESG information. Yet it is unknown whether analysts exhibit similar clienteles – how do analysts respond when facing investors with differing ESG preferences? [3] Moreover, it is unclear whether the anti-ESG movement reflects a general decline in ESG-related sentiment, i.e., a decline in investors' interest in ESG investing, or a divergence, i.e., with non-ESG-oriented investors becoming even less interested in (and potentially even hostile to) ESG investments (Eccles, 2024; Hinchliffe, 2023). In this study, we examine whether ESG-related clienteles exist among sell-side equity analysts, and how the anti-ESG movement differentially impacts the behavior of these analyst clienteles.

We are interested in analyst research for two reasons. First, understanding how analysts respond to ESG reporting amid rising anti-ESG sentiment provides important insights into the

[3] We use the term clienteles to refer to groups of market participants with similar within-group preferences and differing across-group preferences, similarly to dividend clienteles (e.g., Miller and Modigliani, 1961).

broader role of financial intermediaries during a period of rapidly shifting views on ESG issues. Second, analysts act as a proxy for market participants. Examining whether analysts respond with an overall shift or through diverging clientele-like behavior provides insight into whether the anti-ESG movement itself represents an overall shift or divergence.

We exploit the adoption of state-level anti-ESG legislation to capture broader shifts in ESG-related preferences at the state level. The passage of state-level anti-ESG legislation signals strong anti-ESG sentiment in the state. To better capture the initial rise of anti-ESG sentiment, rather than legislative delays, we focus on legislation introduction dates. Our identification strategy exploits firm location – leveraging variation in anti-ESG sentiment across states, and variation in firm locations. Prior literature has shown that investors tend to invest in stocks of firms headquartered in, or with significant activity in, their local area (e.g., Chi and Shanthikumar, 2017; Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005). Thus, we expect that a firm's investors will be disproportionately concentrated in its home state and that analysts covering the firm would be more exposed to shifts in ESG-related sentiment within that state. We use a staggered difference-in-differences design, comparing analyst coverage of firms located in anti-ESG states before and after anti-ESG law introductions to firms in states without such laws.

Our focus is on analyst use of ESG information, in the sense of the relation between analyst coverage characteristics and firms' ESG reporting. Drawing on the framework of Goldstein et al. (2024), we posit that a subset of analysts will behave similarly to Goldstein et al. (2024)'s "green" (ESG-oriented) investors, while another subset will behave similarly to "traditional" (non-ESG-oriented) investors. These investors differ in how they weight financial and ESG information. The model is agnostic as to whether such differences reflect beliefs about the performance implications of ESG or non-pecuniary preferences. If analysts similarly differ in how they interpret and weight

ESG information, they will differ in their use of ESG information. A key question is whether the anti-ESG movement reflects a growing divergence or a decline in ESG preferences. We expect the differences between ESG-oriented and non-ESG-oriented analysts to widen if the anti-ESG movement reflects divergence, and to narrow if it reflects an overall decline in ESG investing.

Before moving to our primary question – how the anti-ESG movement affects analysts' use of ESG-related information – we first shed light on whether analysts differ in apparent ESG orientation. We classify analysts as ESG- and non-ESG-oriented based upon their prior coverage decisions. Specifically, we identify analysts as ESG-oriented if they were more likely to cover firms with strong ESG performance in the prior two years. We show that our classification is (1) persistent, (2) predicts the sensitivity of future coverage initiation and drop decisions to ESG information, and (3) is associated with the extent to which analysts speak about ESG topics on conference calls. We also provide qualitative examples for a subset of analysts, to illustrate the types of ESG orientation which analysts exhibit. Together, these validations suggest that we capture meaningful variation in how analysts use ESG-related information. We use this classification in our primary analyses to shed light on the differing responses of ESG-oriented and non-ESG-oriented analysts to the anti-ESG movement.

To assess the effects of the anti-ESG movement, we first examine whether analysts' coverage of ESG-active firms declines with rising anti-ESG sentiment, considering all analysts. Prior research shows that ESG-reporting firms attract more analyst coverage than non-reporting peers (Dhaliwal, Li, Tsang, and Yang, 2011). When credible and decision-useful, ESG disclosures can provide nonfinancial, forward-looking signals that have the potential to reduce information asymmetry and assist analysts in evaluating firms (Christensen, Hail, and Leuz, 2021). To the extent that the coverage premium is driven by investor preferences for ESG-related investing, the coverage premium for ESG-reporting firms should decline in anti-ESG environments. Examining changes around the introduction of state-level anti-ESG laws, conditional on passing, we find that the coverage premium for ESG-reporting firms declines significantly, suggesting that the coverage premium is, at least in part, driven by a preference for ESG-reporting firms.

We next explore whether analysts cater to distinct ESG-related clienteles, and whether such analyst ESG clienteles diverge or converge in their coverage sensitivity to ESG information in the anti-ESG environment. We find that the decline in ESG coverage for ESG-reporting firms is driven entirely by non-ESG-oriented analysts, while ESG-oriented analysts maintain higher coverage even in the anti-ESG environment. These results point to the emergence and strengthening of distinct ESG clienteles within the analyst community: ESG-oriented analysts continue to cover ESG-reporting firms more heavily even in anti-ESG states, while others reduce such coverage.

Second, we analyze how ESG reporting affects earnings forecast dispersion in anti-ESG environment. Prior research shows that ESG disclosures reduce analyst forecast dispersion, by enhancing information transparency (Dhaliwal et al., 2011) and reducing disagreement among ESG rating agencies (Kimbrough, Wang, Wei, and Zhang, 2024). However, if analysts diverge in their weighting of ESG information, similarly to Goldstein et al. (2024)'s "green" and "traditional" investors, then we might expect a divergence in earnings forecasts. In particular, while ESG disclosures continue to provide potentially relevant information, ESG-oriented and non-ESG-oriented analysts will differ in their interpretation of the performance implications of that information. We find that ESG-reporting firms experience higher dispersion in anti-ESG states, indicating growing divergence in how analysts interpret ESG information.

We further explore the role of ESG-oriented and non-ESG-oriented analysts by examining whether the increase in forecast dispersion is driven by within-group versus across-group dispersion. We find that both ESG-oriented and non-ESG-oriented analysts converge within their own groups when evaluating ESG-reporting firms in anti-ESG states. In particular, within-analyst-group earnings forecast dispersion decreases for ESG-reporting firms relative to non-ESG-reporting firms. However, across-group dispersion rises significantly. Collectively, these results indicate that the overall increase in disagreement is driven by widening differences between ESG-oriented and non-ESG-oriented analysts in their earnings forecasts for ESG-reporting firms. These results suggest that the clienteles differ not only in their preference for ESG-reporting firms, but in their interpretations of the performance implications of that information.

Third, we examine how analyst forecast accuracy changes in anti-ESG environments. Prior research (Dhaliwal, Radhakrishnan, Tsang, and Yang, 2012) finds that analysts covering firms with standalone ESG reports exhibit lower forecast errors, suggesting that ESG reporting enhances the overall information environment, revealing nonfinancial drivers of performance. However, this information may become less predictive of performance in the anti-ESG environment. Moreover, it may even introduce increased noise – making it more difficult for analysts to forecast earnings. In addition, given that ESG-oriented and non-ESG-oriented analysts are likely to respond to ESG information differently, it is an empirical question which of these groups is more accurate ex post. We find that ESG-reporting firms experience larger forecast errors as anti-ESG sentiment intensifies in anti-ESG states. This decline in forecast accuracy is concentrated among non-ESG-oriented analysts. Accuracy remains unchanged for ESG-oriented analysts.

Finally, we examine whether the divergence between ESG-oriented and non-ESG-oriented analysts impacts the information environment of ESG-reporting firms. Using path analysis, we examine the effect of anti-ESG sentiment on information asymmetry and idiosyncratic volatility of ESG-reporting firms, operating through the increased cross-group earnings forecast dispersion we identify, which serves as a proxy for differences of opinion across analyst types. First, focusing on the period around a significant information event, earnings announcements, we find that anti-ESG-induced cross-group dispersion leads to higher abnormal trading volume, and wider effective bid-ask spreads. Second, examining a long-window concurrent effect, we find that cross-group dispersion is associated with higher idiosyncratic volatility, higher abnormal trading volume, and higher effective spreads. Together, these results suggest that the divergence of ESG clienteles is associated with a deterioration in the information environment of ESG-reporting firms.

Overall, our results suggest that ESG information remains financially relevant even in an anti-ESG environment, yet analysts differ markedly in how they use this information. In particular, we observe the rise of ESG-related analyst clienteles. Analysts exhibit significant differences in how their coverage and earnings forecasts respond to ESG-related information, with growing differences in anti-ESG environments. We show that heterogeneous preferences play a significant role in shaping the use of ESG information, and that such information remains relevant to a significant set of market participants even in the anti-ESG environment.

This study makes three main contributions. First, we contribute to the emerging literature on the anti-ESG movement and its implications for capital markets. This stream of work is still nascent, and very little is known about how political and ideological backlash against ESG affects the behavior of capital market participants. To our knowledge, we provide the first large-sample evidence on analyst responses to the anti-ESG movement. Our results reveal that anti-ESG sentiment amplifies differences of opinion across analyst clienteles, consistent with heterogeneous beliefs models in which market participants interpret the same information through different preference lenses (Goldstein et al., 2024), and consistent with the anti-ESG movement reflecting diverging preferences. Resulting differences of opinion have the potential to have significant impact on markets, e.g., on trading volume (Harris and Raviv, 1993; Cookson and Niessner, 2020; Li, Maug, and Schwartz-Ziv, 2022) and stock-price crash risk (Hong and Stein, 2003).

Second, we add to the literature on financial analysts as information intermediaries. In their role as information intermediaries, analysts should logically cater to the preferences of their clients. Analyst coverage, for example, is driven by the firms that their clients are likely to be interested in (Chiu, Lourie, Nekrasov and Teoh, 2021). In a period of increasing polarization of views on a variety of topics, and increasing politicization of firm choices (Kempf and Tsoutsoura, 2024), how information intermediaries respond has significant market implications. Our results indicate that analysts cater to diverging ESG-related preferences, forming analyst ESG-related clienteles. This suggests that information intermediaries may facilitate, rather than mitigate, the divergence of preferences among investors.

Third, our study contributes to the debate on the continuing relevance of ESG information amid political and ideological opposition. The increase in anti-ESG sentiment has caused some to question whether ESG information is still relevant (U.S. SEC, 2025; Tonello, 2025). First, our results indicate that a subset of analysts, ESG-oriented analysts, continue to significantly respond to ESG reporting, covering ESG-reporting firms more heavily and utilizing ESG information in forecasting earnings. Second, while non-ESG-oriented analysts' forecast accuracy declines for ESG-reporting firms after anti-ESG sentiment increases, ESG-oriented analysts' accuracy remains stable. This divergence suggests that, although non-ESG-oriented analysts and their clients may be less interested in ESG information, the underlying informational value of ESG signals persists. This evidence suggests that the financial relevance of ESG information is distinct from its popularity or political acceptability.

II. Institutional Background and Related Literature

Sell-side analysts provide research for their firms' investing clients, in the form of in-depth research reports, shorter research notes, earnings forecasts and other quantitative forecasts, and stock recommendations. They also speak with investors directly and sometimes connect clients with company management (e.g., Green, Jame, Markov, and Subasi, 2014; Brown, Call, Clement, and Sharp, 2015). Clients primarily pay for research indirectly, through trading more heavily with firms which provide helpful research, i.e., through trading commissions (Irvine, 2000; Irvine, 2004; Juergens and Lindsey, 2009; Lehmer, Lourie, and Shanthikumar, 2022). Thus, analysts are incentivized to cover firms which their investing clients are interested in and to build relationships and access to company management, both to inform their research and to provide their clients with access (Malmendier and Shanthikumar, 2014; Richardson, Teoh, and Wysocki, 2004; Green et al., 2014). Therefore, we would expect analysts to rationally respond to shifting investor and company preferences towards ESG. Analysts are also subject to their own behavioral biases, such as decision fatigue and overweighting of "local" information (Hirshleifer, Levi, Lourie, and Teoh, 2019; deHaan, Lee, and Loh 2025). Accordingly, their own preferences and beliefs regarding ESG may also be influenced by shifting societal ESG preferences. In this section, we first review the research on analysts' use of ESG-related information, prior to the anti-ESG movement, and then discuss the emergence and growth of the anti-ESG movement and its potential effects on analyst research.

A. ESG Reporting and Analyst Research

Prior research documents a link between ESG information and analyst research. Christensen, Hail, and Leuz (2021) provide a literature review and economic analysis of ESG reporting and its consequences. As they highlight, research has explored how ESG reporting affects multiple dimensions of analysts' activities (see Section 4.4 of their paper). This subsection summarizes key findings from current literature, focusing on ESG reporting. Existing research focuses on general usage of ESG information, prior to the emergence of the anti-ESG movement.

Dhaliwal et al. (2011) were among the first to show that when firms with strong ESG performance initiate voluntary ESG disclosures, they attract broader analyst coverage and greater institutional investor interest. The authors argue that ESG disclosures reduce information asymmetry between managers and capital market participants by offering decision-useful, nonfinancial signals that complement financial data. Moreover, Dhaliwal et al. (2011) find that analysts following firms with strong ESG performance exhibit lower earnings forecast dispersion after those firms initiate ESG disclosure. Kimbrough et al. (2024) show that ESG reporting reduces forecast dispersion indirectly by decreasing disagreement among ESG rating agencies, which in turn is associated with lower analyst forecast dispersion. In addition, previous literature demonstrates that ESG disclosures help analysts generate more accurate forecasts (e.g., Dhaliwal et al., 2012; Muslu, Mutlu, Radhakrishnan, and Tsang, 2019). Both Dhaliwal et al. (2012) and Muslu et al. (2019) find that firms' issuance of stand-alone ESG reports is associated with lower analyst forecast errors. Together, these studies suggest that ESG reports provide meaningful information that influences analysts' coverage choices and earnings forecasts.[4]

We posit that anti-ESG sentiment will change how analysts use ESG reports. If they view ESG information as less relevant, their coverage and forecasting decisions may be less related to ESG reports. We develop specific predictions for the effects of the anti-ESG movement on analysts' use of ESG information in Section II.C.

[4] Park, Yoon, and Zach (2025) examine the extent to which analyst forecasts incorporate ESG-related risk, and show that analyst forecasts predict future negative ESG incidents. While they do not explicitly examine the use of ESG reports, their results point to analysts using and incorporating ESG-related information.

B. State-Level Anti-ESG Regulations

The rise of ESG-investing in the United States has sparked debate. Many proponents view ESG information as useful for assessing financial risks and long-term stability (i.e., as value-relevant). Other proponents view ESG as consistent with societal values, forcing firms to reduce negative environmental and social externalities they might impose on society, and to increase positive externalities (i.e., as consistent with their values). Critics argue that ESG investing introduces non-financial motives that conflict with traditional investment principles and may reduce financial returns (i.e., that ESG investing is inherently values-driven). This divergence has led to a recent wave of state-level anti-ESG laws regulating how ESG considerations influence investment and contracting decisions by the state.

Current state-level anti-ESG laws vary in scope but generally fall into two categories. Pecuniary-focused regulations require that investment decisions made by public pension funds, retirement systems, and other state financial institutions must rely solely on financial considerations, allowing ESG factors only when financially material. Anti-exclusion regulations restrict the state from contracting with financial institutions and businesses which exclude certain industries, such as fossil fuels or firearms, based on ESG concerns. Together, these approaches reflect broader efforts to curb the influence of ESG in financial markets, either by reaffirming traditional fiduciary priorities or by limiting what opponents view as ideological market restrictions. Both approaches explicitly restrict only values-driven ESG investing.

We use anti-ESG laws as a proxy for the underlying anti-ESG sentiment which prompts them. As of 2024, 19 states had enacted some form of anti-ESG legislation. We use the passage of a state-level anti-ESG law as an indicator of significant anti-ESG sentiment within the state. Passage of a state-level law requires sufficient support in the state legislature, suggesting that state legislators believe that their voters support anti-ESG laws.[5]

The economic effects of anti-ESG regulations are just beginning to be observed. Existing research generally focuses on the direct effects of the laws themselves. For example, Garrett and Ivanov (2024) find that anti-ESG laws in Texas increased municipal bond costs by an estimated \$300–\$500 million due to the withdrawal of major financial institutions from the market. Rajgopal, Srivastava, and Zhao (2025) find that the Texas law is associated with little difference in pension fund investments. We are interested in the effects of underlying anti-ESG sentiment, rather than the laws' direct effects. The laws we examine are not designed to directly regulate analyst research.

C. Hypothesis Development

To develop our hypotheses, we draw on the Goldstein et al. (2024) heterogeneous-beliefs framework, which models how heterogeneous investor preferences, between "green" (ESG-oriented) and "traditional" (non-ESG-oriented) investors, affect how investors interpret and act on ESG-related information. "Green" investors assign greater weight to ESG outcomes, whereas "traditional" investors focus on pecuniary returns. In their framework, performance consists of an ESG-related component and a purely financial component. "Green" and "traditional" investors place different weights on these components, and thus respond differently to signals about ESG performance, even trading in opposing directions on the same ESG information.

We extend these concepts to analysts, proposing that they would likewise differ in how they weight ESG and financial performance. Such differences may reflect analysts' own beliefs about ESG's performance implications or analysts' incentives to cater to investor clienteles with

[5] We contrast the passage of anti-ESG laws with other anti-ESG actions, such as the introduction of an anti-ESG bill, the formation of a committee to examine ESG or anti-ESG issues, or the publication of an anti-ESG letter or statement. While the former requires broad support within a state, the latter can be driven by a small group of politicians or even a single person in a powerful position. Because we are interested in broader anti-ESG sentiment, we focus only on anti-ESG laws which are passed.

different ESG preferences. Similarly to investors, such differences in the weights that analysts place on ESG and financial performance will lead to differences in how they interpret and use ESG information in their research.[6] This sets a baseline for variation in analyst use of ESG information.

The question, then, is how the anti-ESG movement will affect analyst research. The anti-ESG movement implies either a shift in the mix of "green" and "traditional" investors, and/or a shift in the weights that the different types of investors place on ESG performance. As the mix of investors shifts away from "green" investors, and/or as investors' weights on "green" and financial information signals shift, analysts should adjust. Thus, we expect that analysts' research decisions, such as coverage and earnings forecasts, are likely to reflect the shifts in investor preferences signaled by the anti-ESG movement. As a result, analysts should reduce the extent to which they positively respond to ESG-related information.

We further consider how different analyst clienteles – "green" and "traditional" – might respond to the anti-ESG movement. If the anti-ESG movement reflects a shift in the mix of investors away from "green" investors, or a reduction in the weighting of ESG-related performance by "green" investors, then we would expect a larger change in behavior for ESG-oriented analysts, as they correspondingly shift away from ESG-oriented coverage and forecasting strategies. Conversely, if the anti-ESG movement largely reflects a shift in "traditional" investors' weight such that they further reduce the weight they place on ESG performance (or even assign a negative weight to it), then we would expect a stronger change in behavior from non-ESG-oriented analysts. Either way, we should observe an on-average reduction in the weighting of ESG-related

[6] While we posit that analysts will cater to differing clienteles, it is also possible that analysts will not serve investor clienteles in this way, even if investors differ in their preferences. Ravina and Persico (2025) develop a model of mutual fund strategy in an environment with ESG-focused and ESG-neutral investors. They find that large mutual funds will pursue an optimal strategy of adopting moderate ESG-related positions – neither catering to the ESG-focused nor ESG-neutral investors, but choosing an approach in between. If this is the case with analysts, then we should not find evidence of ESG clientele behavior among analysts, nor should we find evidence of ESG-related divergence.

information. It is an empirical question whether such a reduction would be driven by changes among all analysts, or by one particular analyst clientele.

Extending the Goldstein et al. (2024) framework, we expect analysts to reduce their (positive) weighting of ESG information in anti-ESG environments, with potentially heterogeneous effects for ESG-oriented versus non-ESG-oriented analysts. As discussed in the introduction, anti-ESG laws reflect prevailing local attitudes toward ESG and a shift in preferences within affected states. Such shifts were not uniform across the country during our sample period. Given local bias in investing (e.g., Chi and Shanthikumar, 2017; Coval and Moskowitz, 1999; Ivković and Weisbenner, 2005), these shifts should particularly affect analysts covering firms headquartered in anti-ESG states. Thus, we utilize cross-state variation to identify the effects of anti-ESG sentiment, using coverage of firms headquartered in states which have not passed anti-ESG laws as a benchmark for those headquartered in states which have passed such laws.

Specifically, we expect that analysts covering firms in anti-ESG states will be affected by anti-ESG sentiment. In those cases, analysts will have weaker incentives to produce ESG research and are likely to scale back coverage of ESG-reporting firms. Thus, we predict that the traditional coverage premium for ESG-reporting firms should decline in anti-ESG environments. It is an empirical question how the different analyst clienteles will be impacted, as discussed above. Beyond coverage, anti-ESG sentiment has implications for how analysts interpret ESG information when developing forecasts. If ESG-oriented analysts continue using ESG information while others discount it, cross-group divergence should rise. Conversely, if ESG-oriented analysts reduce more, then overall forecast dispersion should fall. The implications for forecast accuracy are similarly ambiguous. If ESG remains economically material despite political backlash, then the group that decreases use of ESG information should experience a decrease in forecast accuracy.

III. Data and Methodology

A. Sample Construction

Our sample covers 2018 to 2024, spanning the rise of the anti-ESG movement. We begin with analyst-level data from I/B/E/S, focusing on firm-year observations of analysts covering U.S.-listed companies. We drop observations with firm headquarters outside of the U.S. Since our study examines the effects of ESG-related factors, we integrate ESG data from Refinitiv, ensuring that only firms with available ESG-related variables are retained. Next, we incorporate firm-level financial and accounting data from Compustat to control for firm characteristics, along with stock price information from CRSP, excluding observations without available control variables or price data. Additionally, singleton observations are excluded to prevent statistical biases arising from isolated firm-year data points. After applying these selection criteria, our final sample consists of 12,661 analyst-firm-year observations. The detailed sample selection procedure is reported in Panel A of Table 1. All continuous variables are winsorized at their 1st and 99th percentile levels to reduce the effects of outliers on our results.

B. Methodology

To analyze how analysts react to increases in anti-ESG sentiment, we employ a staggered difference-in-differences (DiD) approach around the introduction of anti-ESG laws. Treatment firms are those headquartered in states which pass anti-ESG laws.[7] We identify passed anti-ESG bills across U.S. states using the Live Anti-ESG State Action Tracker maintained by Pleiades Strategy and obtain each bill's official introduction date from LegiScan.[8] A key challenge with the

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[7] We are interested in the effects of underlying anti-ESG sentiment, rather than the direct effects of the laws themselves. To improve signal-to-noise, we restrict to bill introductions that ultimately result in enacted law. Conditioning on eventual passage serves to filter out fringe proposals that are unlikely to be viewed as credible by market participants, and that do not capture broader state-level anti-ESG sentiment. This design is analogous to standard practice in financial event studies, which frequently restrict samples to merger announcements that subsequently complete, while treating the announcement date as the event of interest (e.g., Hackbarth and Morellec, 2008).
[8] https://www.pleiadesstrategy.com/pleiades-anti-esg-bill-tracker-state-legislation-attacks-on-responsible-investing.

staggered DiD approach is defining the *Post* variable for control firms in states that never adopted these regulations, as there is no clear event date for these states. To address this issue, we utilize a two-way fixed effects (TWFE) staggered DiD model, following Aghamolla and Li (2018) and Armstrong, Kepler, Samuels, and Taylor (2022). The full model is presented below:

$$y_{it} = \alpha + \beta_1 \, \textit{Anti-ESG}_{it} + \beta_2 \, \textit{ESGReport}_{it} + \beta_3 \, \textit{ESGReport}_{it} \times \textit{Anti-ESG}_{it} + \theta X_{it} + \partial_s + \gamma_t + \upsilon_j + \mu_i + \varepsilon_{it}, \quad (1)$$

where *i* and *t* represent firms and years, respectively. y_{it} is the outcome variable of interest: analyst coverage, forecast dispersion or forecast error. $\textit{Anti-ESG}_{it}$ is an indicator variable equal to one after relevant anti-ESG regulation is introduced in a firm's headquarter state, and zero otherwise. $\textit{ESGReport}_{it}$ is an indicator equal to one if the firm publishes an ESG report, and zero otherwise. The inclusion of state (∂_s; Treat) and year (γ_t; Post) fixed effects represents a generalization of the DiD design, ensuring that results are not affected by potential pre-existing differences in ESG information use across firms in states that introduced anti-ESG regulations at different times.

We construct alternative specifications by including industry fixed effect (υ_j) or stricter firm fixed effect (μ_i) to control for time-invariant industry or firm characteristics. We estimate the model with and without X_{it}, which is a vector of firm-level controls. We estimate the equation using ordinary least squares (OLS) and cluster standard errors at the state level. The main coefficient of interest is β_3, the coefficient on the interaction term $\textit{ESGReport}_{it} \times \textit{Anti-ESG}_{it}$, which measures the change in the relation between analyst outputs and firms' ESG reporting resulting from the introduction of anti-ESG laws, capturing a change in analysts' use of ESG information.

A key innovation in our paper is the examination of potential ESG-related analyst clienteles. Prior literature classifies analysts into different categories/types based on prior behavior, revealed preferences, or personal traits (e.g., Clement and Tse, 2005; Cooper, Day, and Lewis, 2001; Jiang, Kumar, and Law, 2016). Shroff, Venkataraman, and Xin (2014) classify analysts as leader or follower by calculating a leader-follower ratio over a prior two-year window. Hilary and Hsu (2013) use analyst-specific regressions to construct measures of forecast behavior that are subsequently used as explanatory variables in their analyses.

We use an approach which is closest to that used in an additional analysis of Hilary and Hsu (2013) and the approach used in Shroff, Venkataraman, and Xin (2014), which allows for analyst characteristics to vary over time. We classify analyst-year ESG orientation using rolling, analyst-level regressions based on the preceding two years. We define an analyst who is more (less) likely to cover firms with higher ESG scores as an ESG-oriented (non-ESG-oriented) analyst. Prior literature has shown that analysts are more likely to cover firms which they expect to perform well (McNichols and O'Brien, 1997). If ESG-oriented analysts value ESG performance, e.g., viewing it as an important component of overall firm performance, then we expect a more positive relation between their coverage and firms' ESG performance. To measure coverage consistently across firms and years, we construct the dependent variable, *covered*, using a balanced analyst–firm–year panel so that coverage is measured consistently across firms and years.[9] After merging this structure with Refinitiv ESG data, we obtain a balanced panel with 5,201 unique analysts and 4,742 tickers. For each analyst *i* and target year *t*, we estimate the following analyst-level regression using fiscal-year observations from years *t–2* and *t–1*:

$$covered_{i,j,\tau} = \alpha + \beta^{(1)}_{i,j,t} ESGScore_{i,\tau} + \varepsilon_{i,j,\tau} \ , \quad \tau \in \{\, t-2 \,, t-1 \,\} \tag{2}$$

where $covered_{i,j,\tau}$ is the analyst *j*'s coverage indicator for firm *i* in year τ. $ESGScore_{i,\tau}$ is the Refinitiv ESG score for firm *i* in year τ. Using the prior two years makes the analyst-orientation measure in year *t* predetermined with respect to coverage outcomes, mitigating simultaneity

[9] The raw I/B/E/S data are unbalanced and include only cases where an analyst covers a firm, so we first identify firms that appear in Refinitiv ESG and the analysts who have ever covered those firms. We then build the full universe of possible analyst–firm–year combinations and merge in the I/B/E/S coverage flag, setting missing values to zero.

concerns or look-ahead bias. We require each analyst to have at least 30 analyst–firm observations during the window to ensure stable and sufficient coefficient estimates. We then apply the analyst-specific coefficients $\hat{\beta}^{(1)}_{i,j,t}$ from these regressions to the target year *t* and use them to classify analyst *j*. Analyst *j* is defined as ESG-oriented in year *t* if $\hat{\beta}^{(1)}_{i,j,t} > 0$, and as non-ESG-oriented otherwise.

To validate that our classification approach captures a meaningful analyst characteristic, associated with differential use of ESG-related information (similarly to the "green" and "traditional" investors in the Goldstein et al. (2024) framework), we conduct several validations, described in Section III.D, below.

C. Descriptive Statistics

Panel B of Table 1 presents descriptive statistics for the main variables used in the analysis. On average, sample firms are followed by about ten analysts (mean log *Analyst Coverage*=2.098). *Forecast Dispersion* is relatively low overall (mean=0.185), though the standard deviation is large (SD=2.043), indicating substantial heterogeneity across firms. *Forecast Error* has a mean of 0.244 and a standard deviation (SD=3.275), indicating considerable variation in analysts' ex post forecast accuracy. In addition, *Anti-ESG* has a mean of 0.041, meaning that about 4% of analyst-firm-year observations are associated with firms located in states that have introduced anti-ESG legislation. The mean of *ESGReport* is 0.450, suggesting that a substantial share of the firms covered in our sample engage in ESG disclosures. Sample firms are large on average (mean *Size*=13.232), but highly dispersed in terms of size (SD=35.362), consistent with Refinitiv's coverage of all Russell 2000 firms during our sample period. Panel C summarizes the analyst-specific coefficients for each analyst-year: $\hat{\beta}^{(1)}_{i,j,t}$. The distribution is centered near zero (mean=0.016; SD=0.308), and the median is slightly negative (−0.019). Thus, fewer than half of analyst-years exhibit a positive coverage-ESG-score relation. Appendix A provides detailed descriptions of each variable.

D. Validation of ESG- and Non-ESG-Orientation Classification

While we allow for ESG orientation to shift over time for a given analyst, we expect some level of persistence if ESG orientation represents a true analyst characteristic. Thus, we first examine the intertemporal persistence of analyst ESG orientation over one- and two-year horizons. Table 2, Panel A, reports results. We find that 84% of ESG-oriented analysts remain ESG-oriented in the subsequent year, while 86% of non-ESG-oriented analysts remain non-ESG-oriented, with persistence rates of approximately 71% to 72% over a two-year horizon. These results indicate that ESG orientation reflects a stable analyst characteristic rather than transitory variation.

Beyond general persistence, we would expect ESG orientation to affect analysts' decisions to initiate and drop coverage. To examine whether ESG-oriented and non-ESG-oriented analysts differ in the sensitivity of their coverage initiation decisions to ESG information, we construct an analyst-firm-year panel of *potential* initiation. We define initiation as an indicator variable that takes the value 1 if the analyst starts to cover the firm in the given year, and 0 otherwise. To examine drops, we focus on all analyst-firm-years for which the analyst provided coverage in the prior year, and construct an indicator variable that takes the value 1 if the analyst stops covering the firm during the year. We relate these variables to firms' ESG scores or change in ESG scores from the prior year, analyst ESG orientation, and their interaction. The variables of interest are *ESG-Oriented Analyst×ESGScore* and *ESG-Oriented Analyst×ΔESGScore*.

Table 2, Panel B, reports results. We find that ESG-oriented analysts are more likely to initiate coverage of firms with higher ESG scores, relative to non-ESG-oriented analysts, though changes in score do not directly influence coverage initiation. ESG-oriented analysts are more likely to drop coverage of firms with lower ESG or decreasing ESG scores, compared to non-ESG-oriented analysts. Overall, ESG performance has differing effects on the coverage decisions of

ESG-oriented and non-ESG-oriented analysts in the expected directions, consistent with ESG-oriented analysts viewing ESG performance as a more important component of firm performance.

To further validate our classification, we examine whether ESG- and non-ESG-oriented analysts differ in their use of ESG-related language on conference calls. We identify ESG-related discussion using the list of ESG words and phrases developed by Lin, Shen, Wang, and Yu (2024).[10] We examine five measures of analysts' ESG-related speech (e.g., Pak, Eom, Kim, and Park, 2026; Li, Mai, Wong, Yang, and Zhang, 2026). *ESGTalk* is the number of ESG-related words or phrases used by the analyst, normalized by their total word count on a given call. *LnESGTalk* is the log of one plus ESG words-or-phrases count. *Relative_ESGTalk* is the analyst's *ESGTalk* minus the median *ESGTalk* of all analysts speaking on the same call. *Analyst_HasESG* is an indicator equal to one if the analyst mentions ESG-related words on the call, and *Call_HasESG* is an indicator equal to one if any analyst mentions ESG-related words on the same call, capturing whether analysts are more likely to speak on calls with ESG-related analyst questions.

Panel C of Table 2 presents summary statistics for analysts' ESG-related language usage, conditional on speaking on a call, by analyst ESG orientation. ESG-oriented analysts exhibit higher ESG word usage than non-ESG-oriented analysts across all measures, for both the mean and median, with differences statistically significant at the 1% level.

Next, we regress these measures on the ESG-orientation indicator. We control for industry and year fixed effects and cluster standard errors at the firm level. Panel D reports results. We find higher ESG-related language use for four of five measures. In particular, ESG-oriented analysts use more ESG-related language using the *ESGTalk, LnESGTalk,* and *Relative_ESGTalk* measures.

[10] We obtain conference call transcripts from Seeking Alpha and identify portions of the Q&A section when analysts speak. The ESG wordlist includes words such as "climate change," "CO2 emission reduction," "water consumption," "hazardous waste," "child labor," and "diverse workforce," and excludes common words or words with alternative, non-ESG, meaning.

They are also more likely to participate in calls where at least one analyst raises ESG topics.

Finally, we augment these quantitative analyses with a qualitative examination of a subsample of ESG-oriented and non-ESG-oriented analysts. We randomly select fifty analysts from each group, and examine whether analysts reveal a preference for ESG on their LinkedIn pages or through other publicly available information. This qualitative evidence is summarized in Appendix C. We find more frequent examples of ESG-related discussion, skills, conference participation, coverage choices, and other evidence of ESG preferences among analysts classified as ESG-oriented than non-ESG-oriented, supporting that our classification captures a meaningful difference in analysts' views on the importance of ESG.

While our overall classification is likely to be noisy, these validations support that our classification captures meaningful variation in analysts' approach to using ESG information. We use this classification in the remainder of the paper to better understand the differing effects of anti-ESG sentiment on these groups of analysts.

IV. Empirical Results: Analyst Coverage and Earnings Forecasts

A. The Anti-ESG Movement and Analyst Coverage

We first examine whether the anti-ESG movement impacts analysts' weighting of ESG information as measured by their tendency to cover firms with ESG reports. Panel A of Table 3 presents the main regression results for the full sample of analysts. We begin with the baseline specification, which includes *Anti_ESG*, its interaction with ESG information (*ESGReport*), and fixed effects for state, year, and industry, to control for state, industry, and time trends in analyst coverage levels. Column (1) reports the results of this baseline model. Confirming the general coverage premium for ESG reporting firms, the coefficient on *ESGReport* is positive and statistically significant (0.619, $p<0.01$). The coefficient on *Anti-ESG* is negative and statistically significant (-0.083, $p<0.05$), indicating that analyst coverage declines for the average firm headquartered in states where successful anti-ESG laws are introduced. More importantly, the coefficient on the interaction term *ESGReport* × *Anti-ESG* is negative and significant (-0.116, $p<0.01$), implying that the coverage premium for ESG-reporting firms declines in anti-ESG environments.

In column (2), we replace industry fixed effects with firm fixed effects, to focus on within-firm variation. In column (3), we introduce firm-level control variables, such as firm size, profitability, and leverage, to account for time-varying firm characteristics that might influence analyst coverage, along with state, year, and industry fixed effects. Finally, in column (4), we introduce firm fixed effects as well as firm-level control variables. In all three models, the results remain consistent: we find significantly negative coefficients on *ESGReport* × *Anti-ESG*. Economically, the coefficients suggest that, all else equal, ESG-reporting firms experience an approximately 12% drop in analyst coverage following the introduction of successful anti-ESG laws, while non-reporting firms experience an approximately 7% reduction.

A key question of our paper is whether this overall decline is driven by a general shift in ESG preferences among all analysts, a reduction in ESG-oriented analysts' ESG preferences, or a divergence between ESG clienteles. To examine this, we report results from estimating Equation (1) separately for ESG-oriented and non-ESG-oriented analysts, in Table 3, Panel B. Focusing on ESG-oriented analysts, the coefficients on *ESGReport* × *Anti_ESG* are insignificant in columns (1) and (3) with industry fixed effects, and positive and statistically significant in columns (2) and (4) with firm fixed effects. This suggests that ESG-oriented analysts do not change their coverage response to ESG disclosures in anti-ESG environments, or even increase their preference for covering firms which provide ESG information. By contrast, in columns (5) to (8), focusing on non-ESG-oriented analysts, the coefficients on *ESGReport* × *Anti-ESG* are consistently negative and statistically significant.

Comparing columns (4) and (8), including firm fixed effects and controls, we see that ESG-oriented analysts exhibit a coverage premium for ESG-reporting firm-years (positive significant coefficient on *ESGReport*), and this premium increases in anti-ESG environments, with a positive significant interaction. In contrast, non-ESG-oriented analysts do not place a premium on ESG-reporting firms in general (insignificant coefficient on *ESGReport*), and this gap turns negative in anti-ESG environments (the sum of coefficients on *ESGReport* and *ESGReport* × *Anti-ESG* is significantly negative at the 10% level). These results indicate a strengthening of distinct ESG clienteles among analysts: those who show preferences for ESG-related coverage maintain, and even strengthen, their focus on ESG-reporting firms in anti-ESG environments, whereas analysts who do not exhibit such a preference further decrease their coverage for ESG-reporting firms.

B. The Anti-ESG Movement and Earnings Forecast Dispersion

Next, we examine earnings forecast dispersion. If analysts differentially weight and interpret ESG-related information, we might expect forecast dispersion to increase for ESG-reporting firms in anti-ESG environments. Panel A of Table 4 reports results. Column (1) reports the baseline specification with state, year, and industry fixed effects. The interaction term *ESGReport* × *Anti_ESG* is positive and statistically significant (0.097, $p<0.10$), suggesting that ESG-reporting firms experience greater analyst disagreement in anti-ESG environments, consistent with higher variation in how analysts interpret ESG disclosures. The coefficient estimates for the interaction term *ESGReport* × *Anti_ESG* remain positive and significant ($p<0.05$) in columns (2) and (4). Economically, the interaction coefficient in column (4) (0.226) corresponds to an increase of roughly 22% relative to the mean of dispersion (0.185), suggesting a materially higher level of analyst disagreement for ESG-reporting firms in anti-ESG environments.

We next examine whether the higher forecast dispersion for ESG-reporting firms is driven by greater variation within either group of analysts, namely ESG-oriented analysts or non-ESG-oriented analysts, or by greater across-group variation. We quantify cross-group dispersion in analyst forecasts using a one-way ANOVA–style variance decomposition at the firm-year level. For each firm-year, we partition analysts by I(ESG-oriented) $\in\{0,1\}$, compute group means $\overline{V_g}$, variance s_g^2, and count n_g, and decompose the unbiased total cross-sectional variance as

$$s_{total}^2 = \frac{\sum_g (n_g - 1)s_g^2 + \sum_g n_g\left(\overline{V_g} - \bar{V}\right)^2}{N-1}, N = \sum_g n_g\ , \bar{V} = \sum_g \frac{n_g \overline{V_g}}{N} \tag{3}$$

Our measure of cross-group dispersion, $xgroup$, is the between-group share of variance:

$$xgroup = \frac{\sum_g n_g\left(\overline{V_g} - \bar{V}\right)^2}{\sum_g (n_g - 1)s_g^2 + \sum_g n_g\left(\overline{V_g} - \bar{V}\right)^2} \tag{4}$$

i.e., the fraction of total dispersion that is attributable to differences in group means. We then separately analyze each group's within-group dispersion and the across group dispersion. All measures are scaled by stock price for across-firm comparability.

The results are presented in Table 4, Panel B. Columns (1) through (4) present results for within-group dispersion for ESG-oriented analysts. The coefficient estimates on the interaction term *ESGReport* × *Anti_ESG* are consistently negative and statistically significant, suggesting that these analysts actually converge more in their forecasts when evaluating ESG-reporting firms in anti-ESG states. Columns (5) through (8) present results for within-group dispersion for non-ESG-oriented analysts and similarly indicate that non-ESG-oriented analysts converge within-group: the interaction coefficients are negative and significant in three of the four models. Finally, columns (9) through (12) report results for cross-group dispersion, disagreement between ESG-oriented and non-ESG-oriented analysts. Coefficients on *ESGReport* × *Anti_ESG* are positive and statistically significant across all specifications. Thus, the increase in overall dispersion for ESG-reporting firms in anti-ESG environments, documented in Table 4, Panel A, is driven by widening disagreement between ESG- and non-ESG-oriented analysts. These results are consistent with anti-ESG sentiment driving divergence in analyst interpretations of ESG disclosures. This suggests that these ESG-related analyst clienteles differ not only in their preference for covering ESG-reporting firms but also in their forecasts for ESG-reporting firms.

C. The Anti-ESG Movement and Earnings Forecast Errors

Given divergence in earnings forecasts between ESG-oriented and non-ESG-oriented analysts, a natural question is whether one group becomes relatively more accurate. The performance implications of ESG-related information may change in anti-ESG environments. For example, Albuquerque, Koskinen, and Zhang (2019) model CSR investments and show that the profit margin and firm valuation implications of CSR investments depend on consumers' expenditures on CSR-related goods. We might expect such consumer spending behavior to change in anti-ESG environments, and one group of analysts may be more accurate in forecasting relevant performance implications. Moreover, if analysts reallocate effort and focus away from ESG-related information, it may affect forecast accuracy, either positively – if non-ESG information is more relevant – or negatively – if analysts fail to use relevant EGS information. To examine analyst forecast accuracy, we estimate a version of Equation (1), replacing the dependent variable with average earnings forecast error, measured as the mean of the absolute difference between analysts' earnings-per-share (EPS) estimates and actual EPS for a given firm-year, scaled by stock price.

Panel A of Table 5 reports results for the full sample of analysts. Interestingly, coefficients on *Anti_ESG* are negative and statistically significant, indicating more accurate earnings forecasts in anti-ESG environments. However, coefficients on *ESGReport* × *Anti_ESG* are positive and statistically significant across all specifications, indicating that ESG-reporting firms experience larger forecast errors in anti-ESG environments, relative to non-ESG-reporting firms. The magnitude of the column (4) coefficient on *Anti_ESG* (-0.237) indicates that, for non-ESG-reporting firms, forecast error declines by about 97 percent of the average forecast error (0.244). In comparison, the combined effect for ESG-reporting firms (0.066) represents an increase of roughly 27 percent of the average forecast error.

To examine potential differences across analyst types, we examine forecast errors separately for ESG-oriented and non-ESG-oriented analysts. Table 5, Panel B, reports the results. The coefficients on *ESGReport*×*Anti-ESG* are positive and statistically significant in columns (5) through (8), focusing on non-ESG-oriented analysts' forecast errors, whereas they are negative but insignificant in columns (1) through (4), for ESG-oriented analysts. This suggests that non-ESG-oriented analysts become less accurate for ESG-reporting firms after anti-ESG sentiment rises, consistent with underestimating the performance implications of ESG information. In contrast, ESG-oriented analysts exhibit no significant change in their use of ESG information under similar conditions. This is once again consistent with diverging ESG clienteles.[11]

V. Robustness of Main Results

A. Validity of the Parallel Trends Assumption

To provide evidence on the validity of the parallel trends assumption which is implicit in our DiD research design, Figure 1 plots event-time coefficients from a staggered DiD event-time specification. We interact annual event time indicators with the relevant variables, and plot the coefficients on the interaction term, *EventTime*×*ESGReport*. Panels A, B and C present results for

[11] As a robustness test, we examine quarterly earnings forecast accuracy. We continue to find a significantly positive coefficient on *ESGReport*×*Anti-ESG* for non-ESG-oriented analysts, indicating higher forecast errors.

analyst coverage, forecast dispersion, and forecast error, respectively. Coefficients are normalized to zero at the introduction year (τ=0). Across all outcomes, we observe no clear pre-treatment trends, and eight of the nine pre-treatment estimated effects ($\tau = -3, -2, -1$) are statistically indistinguishable from zero, indicating no differential pre-trends in *ESGReport* sensitivity.

Figure 2 decomposes results by analyst type: Panel A shows coverage for ESG-oriented and non-ESG-oriented analysts, Panel B shows within-group forecast dispersion, Panel C shows cross-group forecast dispersion, and Panel D shows forecast error by analyst type. Pre-treatment estimates are again flat, while post-treatment coefficients show divergence across analyst groups.

B. Stacked DiD Analysis

To address potential biases driven by heterogeneity in treatment timing, particularly if treatment effects vary across cohorts (e.g., Callaway and Sant'Anna, 2021), we implement a stacked DiD research design. To construct the stacked DiD sample, we first identify cohorts of firms exposed to anti-ESG sentiment and match each treated firm-years with control firm-years from states that have not passed any anti-ESG bills. For each treatment event, we form an event-specific dataset by appending a clean set of untreated firms as controls. Each event-specific dataset is assigned a unique identifier, and we stack these datasets to form the full testing sample for the stacked DiD estimation. Using this restructured sample, we re-estimate our core regression models. Results for our strictest model, including firm fixed effects and controls, are presented in Table 6. Our main results remain statistically significant in the expected directions for all tests: for analyst coverage (Panel A), forecast dispersion (Panel B), and forecast error (Panel C).

C. Quintiles of ESG-Orientation

While our main analyses focus on ESG-oriented versus non-ESG-oriented analysts, true ESG perspectives likely vary along a continuum. To better understand the responses of analysts over a range of ESG orientation strengths, we partition analysts into quintiles for each year, based on $\hat{\beta}_{i,j,t}^{(1)}$ in Equation (2). The highest (lowest) $\hat{\beta}_{i,j,t}^{(1)}$ quintile includes the analysts with the strongest/most positive (weakest/most negative) ESG orientations. We then re-estimate Equation (1) within each quintile to examine analyst coverage, within-group dispersion, cross-group dispersion (relative to quintile 5 for each quintile in 1 through 4), and average forecast error.

Results are reported in Table 7. Analysts in higher ESG-orientation quintiles (i.e., more positive ESG orientation) are more likely to maintain coverage of ESG-reporting firms, as shown in quintiles 5 through 3, whereas those in lower quintiles (i.e., more negative ESG orientation) are more likely to reduce coverage, as shown in quintiles 2 and 1. Within-group forecast dispersion generally declines. In contrast, cross-group dispersion (relative to quintile 5) rises significantly only for quintile 1, suggesting that growing cross-group earnings forecast dispersion is driven by ESG-orientation extremes. Finally, the increase in earnings forecast errors is significant for analysts in quintiles 2 and 1. Overall, these results are consistent with our main findings.

D. Controlling for General Political Time Trends

A potential concern with our identification approach is that the passage of anti-ESG laws may proxy for broader political trends, rather than ESG-specific sentiment. To address this, we augment our baseline specifications with *Red State*×Year fixed effects. *Red State* equals one in year Y if more than 50% of the state's votes were for the Republican candidate in the most recent presidential election before year Y. Results are untabulated for brevity. Our results are robust to this additional control, suggesting that our findings are not driven by general political time trends.

E. Robustness to Excluding S&P 500 Firms

Ivković and Weisbenner (2005) show that local bias is concentrated in non-S&P 500 firms. Thus, we would expect local sentiment to be more relevant for non-S&P 500 firms. In addition, analysts are likely to have more discretion in their coverage of non-S&P 500 firms. For example, in our data, the median S&P 500 firm-year in our data has 19 analysts covering it, while the median non-S&P 500 firm-year has six. Thus, we replicate our main analyses restricting to the subsample of firm-years which are not in the S&P 500 index. Results are robust (untabulated).

VI. Additional Analyses: Potential Market Impact, and Signed Forecast Errors

A. Potential Market Impact

Our results indicate distinct and diverging ESG clienteles, who differ in their use and interpretation of ESG information. These diverging ESG clienteles increase earnings forecast dispersion. Whether these differences of opinion affect the market is an empirical question.

We first examine the period around earnings announcements. Kim and Verrecchia (1994) model a situation similar to the one in our setting: investors differ in their processing of firm information. They show that when new information arrives, as in an earnings announcement, heterogeneous information processing generates higher abnormal trading volume, increased information asymmetry, and lower liquidity. Motivated by this theory, we examine whether cross-group differences of opinion impact trading volume and bid-ask-spreads around earnings announcements. We predict that higher cross-group earnings-forecast dispersion, as a proxy for higher differences in the use and interpretation of firm-related information, will lead to higher abnormal trading volume and wider bid-ask spreads around earnings announcements.

We use path analysis, similarly to Pevzner, Xie, and Xin (2015) and Jiang, John, Li, and Qian (2018), to examine the direct effect of anti-ESG sentiment on ESG-reporting firms' stocks and the indirect effect via cross-group dispersion. We estimate the following structural model:

$$Cross-Group\ Forecast\ Dispersion_{it} = \alpha_0 + \alpha_1\ AntiESG_{it} + \alpha_2\ ESGReport_{it} + \alpha_3\ ESGReport_{it} * AntiESG_{it} + \theta X_{it} + \partial s + \gamma t + \varepsilon_{it} \quad (5a)$$

$$Y_{it} = \beta_0 + \beta_1\, Cross - Group\ Forecast\ Dispersion_{i,t} + \beta_2\, AntiESG_{it} + \beta_3\, ESGReport_{it} + \beta_4\, ESGReport_{it} * AntiESG_{it} + \theta X_{it} + \partial s + \gamma t + \varepsilon_{it}, \quad (5b)$$

where Y_{it} is the outcome variable of interest, abnormal trading volume or effective spread, over the relevant event window. Abnormal trading volume is defined as the difference between average daily trading volume during the event window and a pre-event benchmark period. Effective spread is constructed following Holden and Jacobsen (2014) as twice the signed difference between the transaction price and the prevailing bid-ask midpoint, aggregated to the daily level using share-volume weights, and then averaged over the event window. Detailed variable definitions are provided in Appendix A. We focus on windows of [-1,1] and [-1,5] trading days around the earnings announcement. $Cross - Group\ Forecast\ Dispersion_{it}$ is measured over the year, capturing general differences of opinion between ESG- and non-ESG-oriented analysts prior to the earnings announcement. Control variables include firm characteristics commonly used in the literature, such as firm size, profitability, leverage, book-to-market, and the earnings surprise rank. Year and state fixed effects are included in all specifications, with standard errors clustered at the state level. All variables are standardized to facilitate interpretation of path coefficients.

Table 8, Panel A, reports results. Columns (1) and (2) report results for abnormal trading volume. The direct path from *ESGReport* × *Anti_ESG* to *AbVol* is insignificant in both windows, indicating that anti-ESG sentiment does not directly affect abnormal trading volume for ESG-reporting firms. Consistent with the results reported in Table 4, Panel B, *ESGReport* × *Anti_ESG* is strongly and positively associated with cross-group forecast dispersion ($p<0.01$). In turn, cross-group dispersion is positively related to abnormal trading volume over the [-1, 5] window ($p<0.10$). The combined indirect effect of anti-ESG sentiment on abnormal trading volume, through cross-group dispersion, is positive and significant at the [-1, 5] window ($p<0.10$).

Columns (3) and (4) report results for effective spread. The direct path from *ESGReport* ×

AntiESG to *EffSprd* is statistically insignificant. Focusing on the indirect path, forecast dispersion is significantly positively associated with effective spread ($p<0.05$) over both windows. The combined indirect effect is positive and significant for both windows ($p<0.10$ or better). These results indicate that anti-ESG-related cross-group dispersion increases effective spreads around earnings announcements, consistent with greater information asymmetry and decreased liquidity.

Theory suggests that differences of opinion will also drive trading volume over long windows (Karpoff, 1986; Varian, 1989). Thus, we examine abnormal trading volume and spreads over a concurrent long window as well. When considering longer-window effects, we further introduce idiosyncratic volatility as an additional outcome variable. As Gillan, Koch and Starks (2021) discuss, ESG can affect firm risk in many ways, for example in mitigating ESG-related downside risks. Becchetti, Ciciretti, and Hasan (2015) find evidence that ESG increases firms' idiosyncratic risk but reduces stakeholder risk. Even without a direct link between ESG and idiosyncratic risk, differences of opinion can generate firm-specific return variation unexplained by systematic risk factors, due to heterogeneous interpretations of the same information.

To examine concurrent long-window effects, we estimate a model similar to Equations (5a) and (5b), but using long-window average abnormal trading volume, average effective bid-ask spreads, and concurrent idiosyncratic volatility as dependent variables. Idiosyncratic volatility (*Ivol*) is measured as the standard deviation of the difference between realized returns and expected returns estimated from the Fama and French (1993) three-factor model. We include the same control variables and fixed effects, with the exception of earnings surprise rank.

Panel B of Table 8 reports results. All three direct effects are statistically insignificant. Consistent with results reported in Table 4, *ESGReport* × *AntiESG* is strongly and positively associated with cross-group forecast dispersion ($p<0.01$). Focusing on the effects of interest, Column (1) reports results for *Ivol*. Cross-group dispersion is positively related to idiosyncratic volatility ($p<0.01$), and the combined indirect effect through cross-group dispersion is positive and significant ($p<0.01$). Columns (2) reports results for abnormal trading volume, and similarly finds a positive and significant indirect effect ($p<0.01$). Finally, Column (3) reports results for effective spreads. While the direct effect of cross-group dispersion on effective spreads is statistically insignificant, the combined path effect is significant at the 10% level. Together, these results indicate that increased cross-group differences of opinion are associated with higher concurrent idiosyncratic volatility, abnormal trading volume, and effective spreads.

Our main results indicate that anti-ESG sentiment drives diverging ESG clienteles – stronger differences of opinion between ESG- and non-ESG-oriented analysts. The results reported in Table 8 are consistent with this divergence having significant effects on market trading.

B. Signed Forecast Errors

In our main analyses, we focus on non-directional impacts of ESG information on analyst research – e.g., examining earnings forecast dispersion and absolute forecast errors. However, we might expect changes in the directional effects of ESG information on ESG- and non-ESG-oriented analyst forecasts as well. In particular, we might expect ESG-oriented (non-ESG-oriented) analysts to be overly optimistic (pessimistic) for ESG-reporting firms. In this section, we examine whether ESG reporting affects ESG- and non-ESG-oriented analysts' *signed* forecast errors – whether they are too optimistic or pessimistic relative to the earnings realization.

Table 9 reports the results. Because we examine signed forecast errors, we expect that the effects of ESG reporting might vary with firms' ESG performance. Thus, we report results for all firms in columns 1 and 4, and separately for firms with below- and above-median ESG scores in columns 2, 3, 5, and 6. Columns 1 through 3 show results for ESG-oriented analysts. We find little evidence of systematic optimism or pessimism, either overall or for high ESG firms. However, for low ESG firms, the coefficient on the interaction term is negative and statistically significant, indicating that ESG-oriented analysts become more pessimistic toward ESG-reporting firms with low ESG performance. Columns (4) through (6) report results for non-ESG-oriented analysts. We find a positive and significant coefficient on the interaction term for all firms, primarily driven by low ESG firms, indicating greater optimism from non-ESG-oriented analysts for ESG-reporting firms with low ESG performance in anti-ESG states. Overall, the results suggest that anti-ESG environments amplify differences in the forecasted performance implications of ESG, with ESG- and non-ESG-oriented analysts exhibiting opposite responses to low ESG performance.

VII. Conclusion

This study examines how the anti-ESG movement reshapes analysts' use and interpretation of ESG information. Using staggered state-level introduction of anti-ESG legislation as a proxy for changes to local ESG sentiment, we show that anti-ESG sentiment attenuates the traditional ESG coverage premium and amplifies heterogeneity in analysts' behaviors and beliefs. We propose and find evidence for emerging, and diverging, ESG-related clienteles among analysts. Non-ESG-oriented analysts reduce coverage of ESG-reporting firms in anti-ESG environments, whereas ESG-oriented analysts maintain coverage. Forecast disagreement between these two groups widens, while within-group dispersion decreases. Additionally, the decline in forecast accuracy for non-ESG-oriented analysts suggests that ESG information remains cash-flow relevant even in an anti-ESG environment, but that analysts have different beliefs regarding the cash-flow implications of ESG.

Our results show that the anti-ESG movement magnifies analyst disagreement, consistent with heterogeneous-beliefs models (Goldstein et al., 2024) and increased divergence between green and traditional investors. We find that this divergence has market consequences for ESG-reporting firms, increasing trading volume, spreads, and volatility. Similarly to Duchin, Farroukh, Harford, and Patel (2024), who find that political divergence decreases mergers and acquisitions, our results imply that ESG backlash reflects not merely a mean shift in preferences but a deeper ESG-related divergence, and that this divergence has real market effects. In a period of increasing ideological polarization, information intermediaries may amplify differences of opinion in capital markets. Moreover, our evidence speaks to the debate on the continuing materiality of ESG information. Even amid political and ideological opposition, ESG-oriented analysts continue to favor covering ESG-reporting firms, and maintain higher forecast accuracy for such firms.

Given growing polarization, we encourage future research to examine the emergence, divergence, and effects of ideological and preference-based clienteles. Considering such clienteles is likely to be increasingly important to understanding financial markets.

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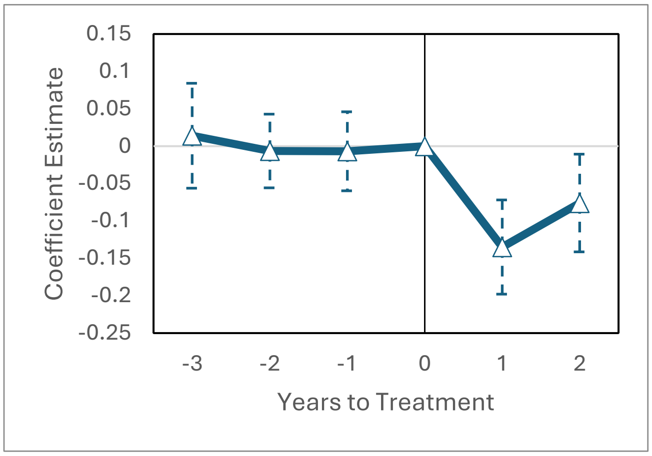
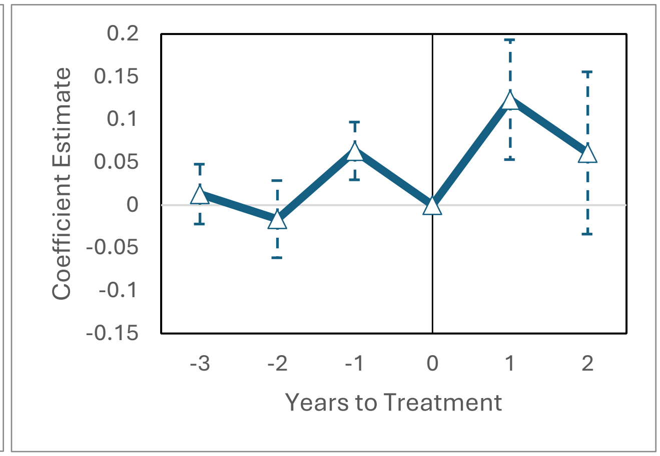
Figure 1
Parallel Trend Assumption

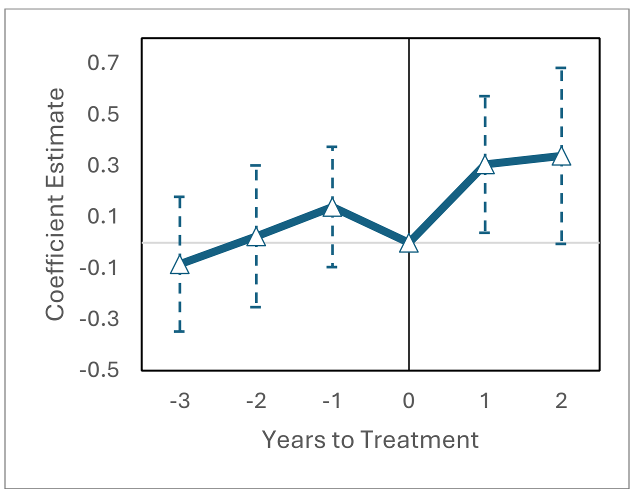
Panel A: Analyst Coverage



Panel B: Forecast Dispersion



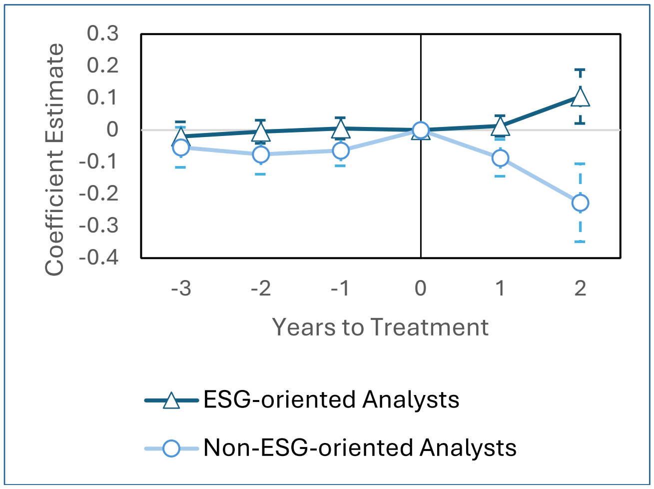
Panel C. Forecast Error



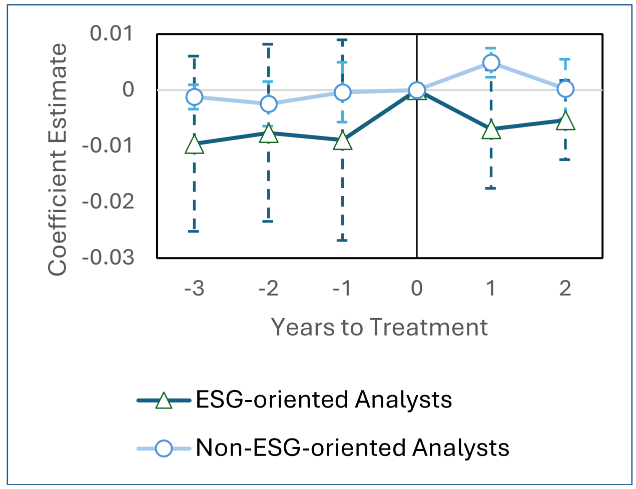
This figure presents the difference-in-difference estimates along with their 95% confidence intervals for analyst coverage (Panel A), forecast dispersion (Panel B), and forecast error (Panel C). The analysis compares firms headquartered in states that introduced anti-ESG legislation with firms in states without such legislation. The year of anti-ESG legislation introduction serves as the reference period (with a coefficient normalized to zero). The coefficients across the periods capture the dynamic effects in the years leading up to and following the introduction of the anti-ESG legislation. Variable definitions are provided in Appendix A.

Figure 2
Parallel Trend Assumption, ESG- and Non-ESG-Oriented Analysts

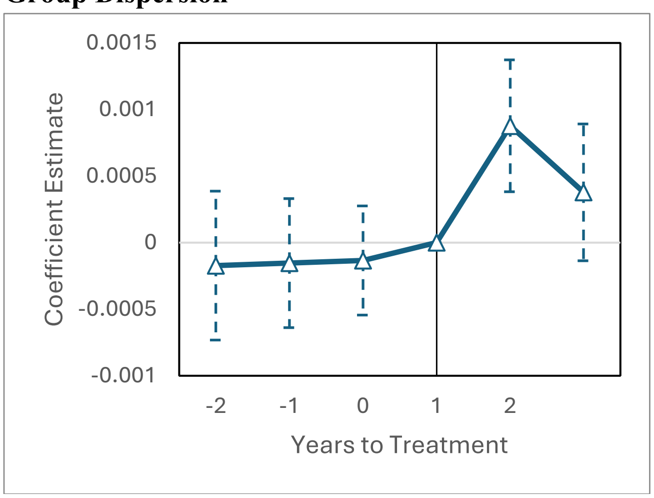
Panel A: Analyst Coverage, ESG-Oriented and Non-ESG-Oriented Analysts



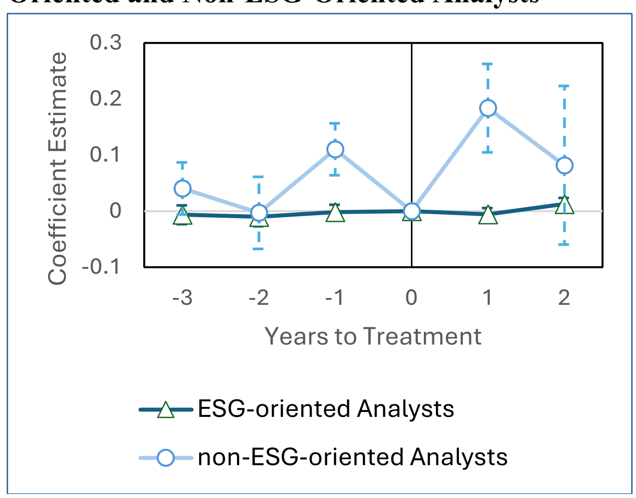
Panel B. Earnings Forecast Dispersion, Within-Group Dispersion



Panel C. Earnings Forecast Dispersion, Cross-Group Dispersion



Panel D. Earnings Forecast Errors, ESG-Oriented and Non-ESG-Oriented Analysts



This figure presents the difference-in-difference estimates along with their 95% confidence intervals for analyst coverage by ESG orientation (Panel A), within-group forecast dispersion (Panel B), cross-group forecast dispersion (Panel C), and forecast error by ESG orientation (Panel D). ESG-oriented and non-ESG-oriented analysts are plotted separately in Panels A and D. Within-group dispersion (Panel B) is calculated separately for ESG-oriented and non-ESG-oriented analysts, while cross-group dispersion (Panel C) captures differences between the two groups. The analysis compares firms headquartered in states that introduced anti-ESG legislation with firms in states without such legislation. The year of anti-ESG legislation introduction serves as the reference period (with a coefficient normalized to zero). The coefficients across the periods capture the dynamic effects in the years leading up to and following the introduction of the anti-ESG legislation. Variable definitions are provided in Appendix A.

Table 1
Sample Composition and Descriptive Statistics

This table provides the sample construction procedure and descriptive statistics. Panel A of this table describes sample selection. Panel B presents descriptive statistics for the main variables used in the sample, which covers 3,066 publicly traded U.S. firms from 2018 to 2024. Panel C reports descriptive statistics for analyst-level ESG coefficients, $\hat{\beta}_{i,j,t}^{(1)}$, estimated from rolling two-year analyst-level regressions of coverage behavior on firms' ESG scores using Equation (2). We classify an analyst-year as ESG-oriented if, in the prior two-year window, the analyst exhibits a positive coefficient on ESG scores, remaining analyst-years are classified as non-ESG-oriented. Appendix A provides detailed descriptions of each variable.

Panel A: Sample Selection

Criteria	Observations
Analysts-firm-year observations from I/B/E/S	344,137
Summarized into ticker-year	34,120
Less: Observations with firms headquarters outside of the U.S.	(14,581)
Less: Observations with missing ESG information from Refinitiv	(6,428)
Less: Observations with missing Compustat control variables	(78)
Less: Observations with missing CRSP stock price data	(10)
Less: Singleton observations	(362)
Total observations in the sample	12,661

Panel B: Firm-Year Level

Variables	N	Mean	S.D.	Q25	Median	Q75
Analyst Coverage	12,661	2.098	0.757	1.609	2.079	2.639
ESG-Oriented Analysts	8,630	1.525	0.615	1.099	1.386	2.079
Non-ESG-Oriented Analysts	8,630	1.505	0.520	1.099	1.609	1.946
Forecast Dispersion	11,546	0.185	2.043	0.003	0.007	0.019
ESG-Oriented Analysts, Within-Group Forecast Dispersion	3,243	0.008	0.028	0.001	0.002	0.007
Non-ESG-Oriented Analysts, Within-Group Forecast Dispersion	3,243	0.007	0.027	0.001	0.002	0.005
Cross-Group Forecast Dispersion	3,243	0.001	0.003	0.000	0.000	0.001
Forecast Error	11,869	0.244	3.275	0.003	0.008	0.023
ESG-Oriented Analyst Forecast Error	6,554	0.029	0.096	0.003	0.007	0.021
Non-ESG-Oriented Analyst Forecast Error	8,779	0.212	2.071	0.004	0.011	0.031
Anti_ESG	12,661	0.041	0.198	0.000	0.000	0.000
ESGReport	12,661	0.450	0.498	0.000	0.000	1.000
Size	12,661	13.232	35.362	0.662	2.350	8.131
ROA	12,661	-0.003	0.224	0.005	0.042	0.093
Leverage	12,661	0.257	0.225	0.051	0.231	0.396
BTM	12,661	0.486	0.483	0.175	0.386	0.710
Volume	12,661	13.537	1.743	12.446	13.615	14.745

Panel C: Analyst-Level

Variables	N	Mean	S.D.	Q25	Median	Q75
$\hat{\beta}_{i,j,t}^{(1)}$(%)	12,884	0.016	0.308	-0.125	-0.019	0.124

Table 2
ESG-Orientation Validation

This table presents results for analyses examining the validity of the ESG-oriented analyst classification, as described in Section III.B. *ESG-Oriented Analyst* (*Non-ESG-Oriented Analyst*) is a binary indicator equal to one if the analyst has a positive (negative) relation between coverage and *ESGScore* based on prior 2-year coverage. Panel A examines the intertemporal persistence of analyst ESG orientation, reporting one- and two-year transition rates. Panel B reports logistic regression results examining whether ESG orientation predicts analysts' subsequent coverage initiation and drop decisions at the analyst–firm–year level. *New Coverage* is a binary indicator equal to one if an analyst begins covering firm in year *t* (having not covered it in year *t−1*), and *Drop Coverage* is a binary indicator equal to one if the analyst ceases coverage in year *t* (having covered it in t−1 but not in t). Initiation regressions are estimated conditional on the analyst not covering the firm in year *t−1*, while drop regressions are estimated conditional on the analyst covering the firm in year *t−1*. *ESGScore* is the firm's ESG performance in year *t*. *ΔESGScore* is the change in the firm's ESG performance from year *t−1* to year *t*. The interaction term *ESG-Oriented Analyst* × *ESGScore* captures whether ESG-oriented analysts are more (less) likely to initiate (drop) coverage of firms with higher ESG performance. Panel C reports summary statistics for variables capturing analysts' ESG-related language on conference calls. ESG-related words are identified through textual analysis of conference call transcripts using the ESG keyword list developed by Lin, Shen, Wang, and Yu (2024). *ESGTalk* is the ratio of an analyst's words-or-phrases count to their total word count on a given call. *LnESGTalk* is the natural logarithm of one plus ESG words-or-phrases count used by an analyst during a call. *Relative_ESGTalk* is an analyst's *ESGTalk* minus the median *ESGTalk* of all analysts speaking on the same call. *Analyst_HasESG* is a binary indicator equal to one if an analyst uses any ESG words during a call. *Call_HasESG* is a binary indicator equal to one if any analyst uses ESG words during the call. Mean (median) differences are based on two-sample t-tests (Wilcoxon rank-sum tests). Panel D tests whether ESG-oriented analysts use more ESG-related words on calls. All include fixed effects indicated in the table. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Appendix A provides detailed descriptions of each variable.

Panel A: Intertemporal Persistence

From → To	t-1 → t (n)	t-1 → t (%)	t-2 → t (n)	t-2 → t (%)
ESG-Oriented Analysts → ESG-Oriented Analysts	3,463	84.42%	1,812	70.86%
ESG-Oriented Analysts → Non-ESG-Oriented Analysts	639	15.58%	745	29.14%
Non-ESG-Oriented Analysts → ESG-Oriented Analysts	707	14.20%	946	27.93%
Non-ESG-Oriented Analysts → Non-ESG-Oriented Analysts	4,273	85.80%	2,441	72.07%

Panel B: New Coverage Initiation and Dropping of Coverage

Variables	(1)	(2)	(3)	(4)
	New Coverage	Drop Coverage	New Coverage	Drop Coverage
ESG-Oriented Analyst	-1.377***	0.325***	0.046**	0.327***
	(0.052)	(0.118)	(0.020)	(0.041)
ESGScore	-1.408***	1.241***		
	(0.084)	(0.219)		
ESG-Oriented Analyst × ESGScore	3.424***	-0.509*		
	(0.114)	(0.281)		
ΔESGScore			-0.021	0.264***
			(0.026)	(0.263)
ESG-Oriented Analyst× ΔESGScore			0.025	-0.277***
			(0.031)	(0.078)
Industry FE	Yes	Yes	Yes	Yes
Likelihood χ^2	1097.951	367.611	147.300	833.890
Observation	28,168,572	16,241	27,747,442	15,994

Table 2 (continued)

Panel C: Summary Statistics of ESG Talk on Conference Calls

	(1)		(2)		(3)		(4)	
Variable	All Analysts (N = 245,707)		ESG-Oriented Analysts (N = 119,547)		Non-ESG-Oriented Analysts (N = 126,160)		Difference (2) − (3)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
ESGTalk	0.134	0.000	0.146	0.000	0.123	0.000	0.023***	0.000***
LnESGTalk	0.141	0.000	0.151	0.000	0.132	0.000	0.019***	0.000***
Relative_ESGTalk	0.068	0.000	0.077	0.000	0.059	0.000	0.018***	0.000***
Analys_HasESG	0.162	0.000	0.172	0.000	0.153	0.000	0.019***	0.000***
Call_HasESG	0.544	1.000	0.591	1.000	0.500	0.000	0.091***	1.000***

Panel D: ESG Talk on Conference Calls and ESG Orientation

	(1)	(2)	(3)	(4)	(5)
Variables	*ESGTalk*	*LnESGTalk*	*Relative_ESGTalk*	*Analyst_HasESG*	*Call_HasESG*
ESG-Oriented Analyst	0.010***	0.004*	0.014***	0.024	0.282***
	(0.002)	(0.002)	(0.002)	(0.017)	(0.020)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	245,707	245,707	245,707	245,707	245,707
R-squared	0.041	0.051	0.006	0.043	0.063

Table 3
Analyst Coverage and ESG Information after Anti-ESG Legislation

This table presents regression results examining the association between analyst coverage, measured as the natural logarithm of one plus the number of analysts covering a firm in a given year, and state-level anti-ESG legislation, ESG reporting, and the interaction between anti-ESG legislation and ESG reporting. Panel A reports the results for the full sample, and Panel B shows the results separately for ESG-oriented and non-ESG-oriented analysts. *Anti_ESG* is an indicator equal to one if the firm is headquartered in a state that has introduced anti-ESG legislation, and zero otherwise. *ESGReport* is an indicator equal to one if the firm publishes an ESG report, and zero otherwise. The interaction term *ESGReport×Anti_ESG* captures whether the effect of ESG disclosure on analyst coverage changes in response to anti-ESG legislative environments. Control variables include firm size (*Size*), return on asset (*ROA*), leverage (*Leverage*), book-to-market ratio (*BTM*), and trading volume (*Volume*). In Panel B, analysts are classified by their ESG orientation. For ESG-oriented analysts, the dependent variable is based on the number of analysts previously identified as responding positively and significantly to ESG scores; for non-ESG-oriented analysts, it is based on the number of remaining analysts not meeting this criterion. All regressions include state and year fixed effects, with additional controls and other fixed effects indicated in the table. Standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Overall Analyst Coverage and ESG Reporting

Variables	(1)	(2)	(3)	(4)
ESGReport×AntiESG	-0.116***	-0.049**	-0.109***	-0.051*
	(0.034)	(0.023)	(0.030)	(0.025)
ESGReport	0.619***	0.016	0.241***	0.023
	(0.017)	(0.016)	(0.016)	(0.016)
Anti_ESG	-0.083**	-0.084***	-0.068*	-0.077***
	(0.032)	(0.025)	(0.037)	(0.027)
Size			0.003***	0.004***
			(0.000)	(0.001)
ROA			0.368***	0.073**
			(0.043)	(0.034)
Leverage			-0.046	0.031
			(0.047)	(0.051)
BTM			-0.176***	0.016
			(0.026)	(0.022)
Volume			0.203***	0.052***
			(0.006)	(0.006)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	12,661	12,661	12,661	12,661
R-squared	0.336	0.874	0.567	0.876

Table 3 (continued)

Panel B. Analyst Coverage by ESG Orientation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	*ESG-Oriented Analysts Coverage*				*Non-ESG-Oriented Analysts Coverage*			
ESGReport×AntiESG	-0.067	0.063*	-0.052	0.065*	-0.101**	-0.089**	-0.130***	-0.081**
	(0.042)	(0.034)	(0.046)	(0.036)	(0.043)	(0.040)	(0.039)	(0.040)
ESGReport	0.518***	0.039**	0.256***	0.043**	0.088***	0.009	-0.023**	0.011
	(0.018)	(0.017)	(0.010)	(0.017)	(0.011)	(0.013)	(0.010)	(0.012)
Anti_ESG	0.001	-0.075***	-0.010	-0.073***	-0.009	0.020	0.014	0.017
	(0.032)	(0.024)	(0.025)	(0.023)	(0.044)	(0.038)	(0.040)	(0.038)
Control variables	No	No	Yes	Yes	No	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	8,629	8,613	8,630	8,613	8,629	8,611	8,629	8,611
R-squared	0.301	0.861	0.510	0.861	0.198	0.767	0.300	0.769

Table 4
Earnings Forecast Dispersion and ESG Information after Anti-ESG Legislation

This table presents regression results examining the association between earnings forecast dispersion and state-level anti-ESG legislation, ESG reporting, and the interaction between anti-ESG legislation and ESG reporting. Panel A reports the results for the full sample, and Panel B shows the results separately for dispersion decomposed into ESG-oriented and non-ESG-oriented analysts within-group dispersion and cross-group dispersion between the two. To ensure reliability, dispersion is calculated only when at least three analyst forecasts are available. *Anti_ESG* is an indicator equal to one if a state has introduced anti-ESG legislation, and zero otherwise. *ESGReport* is an indicator for whether the firm publishes an ESG report, and zero otherwise. The interaction term *ESGReport×Anti_ESG* captures whether the informativeness of ESG disclosure varies in states with anti-ESG environments. In Panel B, the dependent variables are three dispersion measures at the firm-year level. *ESG-Oriented Analysts, Within-Group Forecast Dispersion* is the cross-sectional standard deviation of forecasts issued by analysts classified as ESG-oriented, scaled by the firm's stock price; *Non-ESG-Oriented Analysts, Within-Group Forecast Dispersion* is defined analogously for the non-ESG group, scaled by the firm's stock price. *Cross-group Forecast Dispersion* isolates the between-group component of total dispersion, the portion attributable to differences between the two groups' average forecasts, computed via a one-way variance decomposition using group means and sizes, and scaled by the firm's stock price. All regressions include state and year fixed effects. Additional control variables include firm characteristics such as *Size*, *ROA*, *Leverage*, *BTM*, and *Volume*, and additional fixed effects as indicated. Standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Overall Earnings Forecast Dispersion

Variables	(1)	(2)	(3)	(4)
ESGReport×AntiESG	0.097*	0.227**	0.062	0.226**
	(0.054)	(0.100)	(0.051)	(0.104)
ESGReport	-0.216***	-0.016	-0.052	-0.011
	(0.049)	(0.014)	(0.075)	(0.012)
Anti_ESG	-0.020	-0.156*	-0.026	-0.162*
	(0.032)	(0.079)	(0.050)	(0.082)
Size			-0.000	0.000
			(0.000)	(0.000)
ROA			-2.259***	0.017
			(0.476)	(0.359)
Leverage			-0.188	0.284
			(0.155)	(0.183)
BTM			-0.137	-0.269*
			(0.084)	(0.154)
Volume			0.022	0.023
			(0.023)	(0.050)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	11,545	11,546	11,545	11,546
R-squared	0.020	0.852	0.063	0.853

Table 4 (continued)

Panel B. Within-Group and Cross-Group Forecast Dispersion by Analyst ESG Orientation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ESG-Oriented Analysts, Within-Group Forecast Dispersion				*Non-ESG-Oriented Analysts, Within-Group Forecast Dispersion*				*Cross-Group Forecast Dispersion*			
ESGReport×AntiESG	-0.006*	-0.008***	-0.008*	-0.010*	-0.007**	-0.006***	-0.008**	-0.005	0.001***	0.001**	0.001***	0.001**
	(0.004)	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
ESGReport	-0.000	0.000	0.001	0.002	-0.000	0.005	0.001	0.005	-0.001***	-0.000**	-0.000***	-0.000**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Anti_ESG	0.005	0.005	0.008*	0.007	0.010**	0.008**	0.012**	0.008	-0.001***	-0.000	-0.001***	-0.000
	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3,242	3,243	3,242	3,243	3,242	3,243	3,242	3,243	3,242	3,243	3,242	3,243
R-squared	0.109	0.425	0.166	0.502	0.105	0.465	0.136	0.475	0.053	0.468	0.075	0.468

Table 5
Earnings Forecast Error and ESG Information after Anti-ESG Legislation

This table presents the results of regressions examining the association between analyst forecast error, defined as the mean of absolute difference between analysts' earnings estimates and actual earnings for a given firm-year, normalized by share price, and state-level anti-ESG legislation, ESG reporting, and the interaction between anti-ESG legislation and ESG reporting. Panel A reports the results for the full sample, and Panel B shows the results separately for ESG-oriented and non-ESG-oriented analysts. *Anti_ESG* is an indicator equal to one if a state has introduced anti-ESG legislation, and zero otherwise. *ESGReport* is an indicator for whether the firm publishes an ESG report, and zero otherwise. The interaction term *ESGReport×Anti_ESG* captures whether the informativeness of ESG disclosure varies in states with anti-ESG environments. In Panel B, analysts are classified by their orientation toward ESG. The dependent variables are the two forecast error measures at the firm-year level. *ESG-Oriented Analyst Error* is the cross-sectional mean of absolute difference between actual earnings and earnings estimates issued by analysts classified as ESG-oriented, scaled by the firm's stock price; *Non-ESG-Oriented Analyst Error* is defined analogously for the non-ESG group, scaled by the firm's stock price. All regressions include state and year fixed effects. Additional control variables include firm characteristics such as *Size*, *ROA*, *Leverage*, *BTM*, and *Volume*, and additional fixed effects as indicated. Standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Overall Earnings Forecast Error

Variables	(1)	(2)	(3)	(4)
ESGReport×AntiESG	0.270***	0.312***	0.218**	0.303**
	(0.085)	(0.108)	(0.106)	(0.136)
ESGReport	-0.343***	-0.022	-0.145	-0.012
	(0.085)	(0.031)	(0.117)	(0.024)
Anti_ESG	-0.175**	-0.236***	-0.174*	-0.237**
	(0.066)	(0.080)	(0.103)	(0.114)
Size			-0.001	0.000
			(0.001)	(0.001)
ROA			-3.048***	0.280
			(0.697)	(0.812)
Leverage			-0.305	0.175
			(0.209)	(0.225)
BTM			-0.201	-0.429*
			(0.174)	(0.245)
Volume			0.066	0.070
			(0.047)	(0.131)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Observations	12,252	11,869	12,252	11,869
R-squared	0.016	0.758	0.044	0.759

Table 5 (continued)

Panel B. Analyst Forecast Error by ESG Orientation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ESG-Oriented Analyst Forecast Error				*Non-ESG-Oriented Analyst Forecast Error*			
ESGReport×AntiESG	-0.021	-0.026	-0.021	-0.023	0.237***	0.273*	0.194**	0.284**
	(0.025)	(0.041)	(0.023)	(0.042)	(0.080)	(0.139)	(0.080)	(0.139)
ESGReport	-0.019***	0.003	-0.013***	0.003	-0.282***	-0.038	-0.099	-0.027
	(0.004)	(0.004)	(0.004)	(0.004)	(0.070)	(0.023)	(0.085)	(0.017)
Anti_ESG	0.030	0.028	0.034	0.027	-0.066	-0.204*	-0.056	-0.224*
	(0.024)	(0.038)	(0.021)	(0.038)	(0.078)	(0.119)	(0.082)	(0.116)
Control Variables	No	No	Yes	Yes	No	No	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	6,545	6,534	6,545	6,543	8,765	8,717	8,765	8,729
R-squared	0.009	0.215	0.015	0.232	0.027	0.839	0.072	0.841

Table 6
Stacked DiD Analysis

This table presents the results of a stacked difference-in-differences (DiD) analysis examining how anti-ESG sentiment affects analyst behavior in response to ESG information. Following best practice for staggered adoption, we form cohort-specific event-time datasets by matching each treated firm-year to controls in the same event year, stack cohorts, and include introduction-cohort fixed effects. In Panel A, the dependent variables are analyst coverage measures, including total analyst coverage and coverage by ESG-oriented and non-ESG-oriented analysts, each measured as the natural logarithm of one plus the number of analysts covering a firm in a given firm-year. Panel B reports results for forecast dispersion, including total dispersion, ESG-oriented dispersion, non-ESG-oriented dispersion, and cross-group dispersion, where dispersion is defined as the standard deviation of analysts' earnings estimates for a firm-year and scaled by stock price. Panel C reports forecast error measures, including total forecast error, ESG-oriented analyst error, and non-ESG-oriented analyst error, defined as the mean absolute difference between analysts' earnings estimates and actual earnings, scaled by stock price. *Anti_ESG* equals one if the firm is headquartered in a state that has introduced an anti-ESG statute, and zero otherwise. *ESGReport* equals one if the firm publishes a standalone ESG/sustainability report. *ESGReport* × *Anti_ESG* captures whether analyst responses to ESG disclosure differ in anti-ESG environments. Additional interaction terms and specifications (e.g., analyst-type partitions and cross-group measures) follow the definitions provided in prior tables. All regressions include state and year fixed effects; introduction-cohort fixed effects are included by construction. Control variables and any additional fixed effects (e.g., firm or industry) are listed in the table. Continuous variables are winsorized at the 1st/99th percentiles. Standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Analyst Coverage

	(1)	(2)	(3)
Variables	*Analyst Coverage*	*ESG-Oriented Analysts Coverage*	*Non-ESG-Oriented Analysts Coverage*
ESGReport×AntiESG	-0.070***	0.065*	-0.079***
	(0.019)	(0.037)	(0.029)
ESGReport	0.019	0.026**	0.012
	(0.012)	(0.012)	(0.013)
Anti_ESG	-0.070**	-0.070***	0.023
	(0.032)	(0.023)	(0.033)
Control Variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Observations	130,958	90,511	90,511
R-squared	0.940	0.898	0.816

Table 6 (continued)

Panel B: Forecast Dispersion

	(1)	(2)	(3)	(4)
Variables	*Forecast Dispersion*	*ESG-Oriented Analysts, Within-Group Forecast Dispersion*	*Non-ESG-Oriented Analysts, Within-Group Forecast Dispersion*	*Cross-Group Forecast Dispersion*
ESGReport×AntiESG	0.476***	-0.011***	-0.005	0.001***
	(0.168)	(0.003)	(0.003)	(0.000)
ESGReport	-0.010	0.002	0.007	-0.000
	(0.016)	(0.001)	(0.005)	(0.000)
Anti_ESG	-0.381***	0.005	0.008	-0.000**
	(0.135)	(0.003)	(0.005)	(0.000)
Control Variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
Observations	153,901	44,760	44,749	44,758
R-squared	0.880	0.979	0.972	0.699

Panel C: Forecast Error

	(1)	(2)	(3)
Variables	*Forecast Error*	*ESG-Oriented Analyst Forecast Error*	*Non-ESG-Oriented Analyst Forecast Error*
ESGReport×AntiESG	0.687**	-0.016	0.600***
	(0.296)	(0.034)	(0.130)
ESGReport	-0.004	-0.000	0.003
	(0.042)	(0.003)	(0.053)
Anti_ESG	-0.637**	0.022	-0.484***
	(0.264)	(0.031)	(0.086)
Control Variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Observations	162,661	93,332	128,474
R-squared	0.799	0.810	0.941

Table 7
Quintiles of ESG-Orientation

This table presents results by analyst ESG-orientation quintiles, examining how anti-ESG sentiment affects analyst behavior in response to ESG information. Quintiles are constructed annually based on analysts' estimated ESG-orientation coefficients from Equation (2), where Quintile 5 (Quintile 1) includes analysts with the most positive (most negative) ESG orientation. For each outcome, we construct quintile-specific measures at the firm–year level. Analyst coverage is measured as the number of analysts in each quintile. Within-group forecast dispersion is computed as the standard deviation of forecasts within each quintile, requiring at least three analysts. Cross-group dispersion is constructed by comparing Quintile 5 to each of the other quintiles (Quintiles 1 – 4) within the same firm announcement. Forecast error is measured as the average absolute forecast error within each quintile, requiring at least two forecasts. We then estimate Equation (1) separately for each quintile-based measure. For brevity, the table reports only the coefficient on the interaction term (*ESGReport×AntiESG*), along with standard errors. All regressions include the full set of control variables and fixed effects as indicated in the specification. Standard errors clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Variables	Quintile 5, most positive ESG-orientation	Quintile 4	Quintile 3	Quintile 2	Quintile 1, most negative ESG-orientation
Analyst Coverage	0.040	0.061	0.070*	-0.111***	-0.107***
	(0.033)	(0.040)	(0.036)	(0.031)	(0.027)
Within-Group Forecast Dispersion	-0.005***	-0.009**	-0.004*	-0.002	-0.007***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
Cross-Group Forecast Dispersion		-0.000	-0.000	-0.001	0.001**
(relative to Quintile 5)		(0.001)	(0.001)	(0.001)	(0.001)
Forecast Error	-0.002	-0.014	0.013	0.291**	0.379*
	(0.004)	(0.031)	(0.008)	(0.113)	(0.201)

Table 8
Cross-Group Analyst Forecast Dispersion, Post-Announcement Market Outcomes: Path Analysis

This table reports maximum likelihood estimates from structural equation models examining the relation between cross-group analyst forecast dispersion and market outcomes measured both in short trading-day windows around earnings announcements and over the concurrent inter-announcement period. The structural system consists of two equations modeling (i) cross-group forecast dispersion and (ii) market responses within a path analysis framework. Panel A focuses on short-window market reactions around earnings announcements. The outcome variables are abnormal trading volume (*AbVol*) and effective spread (*EffSprd*), measured over trading-day event windows [−1, 1] and [−1, 5] relative to the earnings announcement date (day 0). Abnormal trading volume is defined as the difference between average trading volume during the event window and normal trading volume over the pre-event window [−60, −11]. Effective spreads are computed as share-volume–weighted daily effective spreads based on deviations of transaction prices from the prevailing NBBO midpoint, following Holden and Jacobsen (2014), and averaged over the same event windows. Panel B examines concurrent long-window effects over the inter-announcement period. The outcome variables are idiosyncratic volatility (*Ivol*), abnormal trading volume (*AbVol*), and effective spread (*EffSprd*), measured over the trading-day window between the prior and current annual earnings announcements. Idiosyncratic volatility is defined as the standard deviation of residual returns from firm-specific Fama–French (1993) three-factor models estimated over this interval. Abnormal trading volume is defined as the difference between average trading volume over the current interval and that over the preceding interval. Effective spreads are computed analogously as averages of daily spreads over the same concurrent window. All specifications include firm, state, and year fixed effects, as well as controls for *Size*, *ROA*, *Leverage*, *BTM*, and earning surprise. Each variable included in the structural equations is standardized. Standard errors clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Subsequent Earnings Announcement Window Effects

	(1)	(2)	(3)	(4)
Path / Effect	*AbVol*[-1,1]	*AbVol*[-1,5]	*EffSprd*[-1,1]	*EffSprd*[-1,5]
Direct Path				
P(*ESGReport×AntiESG*,*MktOutcome*)	-0.012	0.009	-0.019	-0.012
	(0.022)	(0.028)	(0.015)	(0.015)
Mediated Path				
P(*ESGReport×AntiESG*, *Cross-Group Forecast Dispersion*)	0.070***	0.070***	0.070***	0.070***
	(0.016)	(0.016)	(0.016)	(0.016)
P(*Cross-Group Forecast Dispersion*, *MktOutcome*)	0.025	0.043*	0.082**	0.093**
	(0.025)	(0.022)	(0.037)	(0.037)
Total Mediated Path Effect				
P(*ESGReport×AntiESG*, *Cross-Group Forecast Dispersion*) × P(*Cross-Group Forecast Dispersion*, *MktOutcome*)	0.016	0.028*	0.332*	0.319**
	(0.016)	(0.016)	(0.171)	(0.159)
Number of observations	2,823	2,823	2,823	2,823

Table 8 (continued)

Panel B: Concurrent Long-Window Effect

	(1)	(2)	(3)
Path / Effect	*Ivol*	*AbVol*	*EffSprd*
Direct Path			
P(*ESGReport*×*AntiESG*,*MktOutcome*)	0.002	0.008	0.024
	(0.020)	(0.024)	(0.022)
Mediated Path			
P(*ESGReport*×*AntiESG*, *Cross-Group Forecast Dispersion*)	0.083***	0.083***	0.083***
	(0.016)	(0.016)	(0.016)
P(*Cross-Group Forecast Dispersion*, *MktOutcome*)	0.134***	0.070***	0.045
	(0.029)	(0.015)	(0.038)
Total Mediated Path Effect			
P(*ESGReport*×*AntiESG*, *Cross-Group Forecast Dispersion*) ×	0.001***	0.070***	0.385*
P(*Cross-Group Forecast Dispersion*, *MktOutcome*)	(0.000)	(0.021)	(0.200)
Number of observations	1,505	1,505	1,505

Table 9
Signed Forecast Error and ESG Information after Anti-ESG Legislation, Analyst Forecast Optimism/Pessimism

This table presents the results of regressions examining the association between signed forecast errors and state-level anti-ESG legislation, conditional on firms' ESG disclosure and analysts' ESG orientation. Signed forecast error is defined as the difference between the analyst's earnings forecast and actual earnings, scaled by stock price, computed separately for ESG-oriented and non-ESG-oriented analysts. Columns (1) through (3) present results for ESG-oriented analysts, and columns (4) through (6) present results for non-ESG-oriented analysts. Within each group, we report results for all firms, as well as separately for firms with below- and above-median ESG scores (low ESG and high ESG firms, respectively), based on the annual distribution of ESG scores. *Anti_ESG* is an indicator equal to one if a state has introduced anti-ESG legislation, and zero otherwise. *ESGReport* is an indicator for whether the firm publishes an ESG report. The interaction term *ESGReport×Anti_ESG* captures whether the effect of ESG disclosure varies in states with anti-ESG environments. All regressions include firm, state, and year fixed effects. Control variables include firm characteristics such as *Size*, *ROA*, *Leverage*, *BTM*, and *Volume*. Standard errors clustered at the state level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ESG-Oriented Analysts			Non-ESG-Oriented Analysts		
Variables	All Firms	Low ESG firms	High ESG firms	All Firms	Low ESG firms	High ESG firms
ESGReport×AntiESG	0.001	-0.050**	-0.003	0.110***	0.206***	0.005
	(0.028)	(0.022)	(0.006)	(0.037)	(0.051)	(0.005)
ESGReport	0.001	-0.004	-0.001	-0.028**	-0.039*	-0.004
	(0.004)	(0.007)	(0.006)	(0.012)	(0.021)	(0.004)
Anti_ESG	-0.015	0.015	0.004	-0.133***	-0.201***	-0.008
	(0.033)	(0.036)	(0.005)	(0.030)	(0.056)	(0.005)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,543	2,993	3,060	8,729	3,977	3,987
R-squared	0.232	0.185	0.406	0.612	0.571	0.948

Appendix A. Variable Definition

Analyst output variables	
Analyst Coverage	The natural logarithm of one plus the number of analysts covering a firm in a given year.
ESG-Oriented Analysts Coverage	The natural logarithm of one plus the number of analysts classified as ESG-oriented who issue earnings forecast for a firm in a given year. Analyst classification follows the ESG-oriented definition described in the main text.
Non-ESG-Oriented Analysts Coverage	The natural logarithm of one plus the number of analysts not classified as ESG-oriented who issue earnings forecast for a firm in a given year. Analyst classification follows the non-ESG-oriented definition described in the main text.
Forecast Dispersion	The standard deviation of analysts' EPS estimates for a given firm-year, scaled by the firm's stock price. Dispersion is calculated only when at least three analyst forecasts are available.
ESG-Oriented Analysts, Within-Group Forecast Dispersion	The standard deviation of EPS forecasts issued by ESG-oriented analysts for a given firm-year, scaled by the firm's stock price. This measure is computed only when at least three ESG-oriented analyst forecasts are available.
Non-ESG-Oriented Analysts, Within-Group Forecast Dispersion	The standard deviation of EPS forecasts issued by non-ESG-oriented analysts for a given firm-year, scaled by the firm's stock price. This measure is computed only when at least three ESG-oriented analyst forecasts are available.
Cross-Group Forecast Dispersion	The between-group component of overall forecast dispersion, using a one-way ANOVA decomposition at the firm-year level. For each firm-year, we partition analysts according to the indicator variable $g = I(\text{ESG-oriented}) \in \{0,1\}$. Let n_g, $\bar{V}_g$, and s_g^2, denote group size, mean forecast, and sample variance, and let $\bar{V}$ be the overall mean with $N = \sum_g n_g$. We define cross-group dispersion as the between-group share of total variation: $$xgroup = \frac{\sum_g n_g \left(\bar{V}_g - \bar{V}\right)^2}{\sum_g \left(n_g - 1\right) s_g^2 + \sum_g n_g \left(\bar{V}_g - \bar{V}\right)^2}$$ The measure is computed for firm-years and is scaled by the firm's stock.
Forecast Error	The mean of absolute difference between analysts' EPS estimates and actual EPS at the upcoming fiscal year-end for a given firm-year, scaled by the firm's stock price.
ESG-Oriented Analyst Forecast Error	The mean of absolute difference between analysts' EPS estimates issued by ESG-oriented analysts and actual EPS at the upcoming fiscal year-end for a given firm-year, scaled by the firm's stock price.
Non-ESG-Oriented Analyst Forecast Error	The mean of absolute difference between analysts' EPS estimates issued by non-ESG-oriented analysts and actual EPS at the upcoming fiscal year-end for a given firm-year, scaled by the firm's stock price.
ESG-Oriented Analyst Signed Forecast Error	The mean of analysts' EPS estimates issued by ESG-oriented analysts minus actual EPS at the upcoming fiscal year-end for a given firm-year, scaled by the firm's stock price.

Non-ESG-Oriented Analyst Signed Forecast Error	The mean of analysts' EPS estimates issued by non-ESG-oriented analysts minus actual EPS at the upcoming fiscal year-end for a given firm-year, scaled by the firm's stock price.
ESG variables	
ESGScore	The firm-level ESG score from Refinitiv, a composite percentile-ranked measure of environmental, social, and governance performance based on publicly information and benchmarked relative to peer firms.
ESGReport	An indicator variable that coded as one if a firm release CSR/ESG reporting in year *t*, and zero otherwise, based on Refinitiv.
Anti-ESG	An indicator variable that equal to one for the time after the introduction of anti-ESG regulations in states where a firm is headquartered, and zero otherwise.
ESG-Oriented Analysts	An indicator variable equal to one if analyst *i* is classified as ESG-oriented in year *t*, and zero otherwise. An analyst is classified as ESG-oriented if the estimated coefficient on *ESGScore* from the rolling analyst-level regression specified in Equation (2), using observations from the prior two fiscal years, is positive.
Non-ESG-Oriented Analysts	An indicator variable equal to one if analyst *i* is classified as non-ESG-oriented in year *t*, and zero otherwise. An analyst is classified as non-ESG-oriented if the estimated coefficient on ESGScore from the rolling analyst-level regression in Equation (2) is negative.
Market outcome variables	
EffSprd[-1,1], EffSprd[-1,5]	Post–earnings announcement effective spread. Using TAQ data and following Holden and Jacobsen (2014), trade-level effective spreads are computed based on the deviation of transaction prices from the prevailing NBBO midpoint, with trade direction determined using Lee and Ready (1991). Daily spreads are aggregated as share-volume–weighted averages across trades, and EffSprd is defined as the average of these daily values over event windows [−1,1] and [−1,5] relative to the earnings announcement date (day 0).
AbVol[-1,1], AbVol[-1,5]	Post–earnings announcement abnormal trading volume measured over trading-day event windows around annual earnings announcements. Daily trading volume is obtained from CRSP, and normal volume is defined as the average trading volume over the pre-event window [−60,−11] trading days relative to the earnings announcement date (day 0). Abnormal trading volume is computed as the difference between average trading volume over event windows [−1,1] and [−1,5] and the corresponding normal volume, and the measure is expressed in logarithmic form.
Ivol	Idiosyncratic return volatility measured over the concurrent trading-day window between the prior and current annual earnings announcements. Expected returns are obtained from firm-specific Fama–French (1993) three-factor models estimated using daily excess returns within this interval. Abnormal returns are computed as residuals from these models, and idiosyncratic volatility is defined as the standard deviation of residual returns over the concurrent trading-day window between the prior and current annual earnings announcements.

EffSprd	Effective spread measured over the concurrent trading-day window between the prior and current annual earnings announcements. Using TAQ data and following Holden and Jacobsen (2014), daily effective spreads are computed as share-volume–weighted averages of trade-level spreads. The measure is defined as the average of daily effective spreads over the concurrent trading-day window between the prior and current annual earnings announcements.
AbVol	Abnormal trading volume measured over the concurrent trading-day window between the prior and current annual earnings announcements. Daily trading volume is obtained from CRSP, and abnormal volume is defined as the difference between average trading volume over the current interval and that over the preceding interval, and expressed in logarithmic form.
Conference call variables	
ESGTalk	The ratio of an analyst's ESG words-or-phrases count to their total word count on a given earnings conference call, multiplied by 100. ESG words-or-phrases are identified through textual analysis of conference call transcripts using the ESG keyword list developed by Lin, Shen, Wang, and Yu (2024).
LnESGTalk	The natural logarithm of one plus the number of ESG words-or-phrases used by an analyst during a call.
Relative_ESGTalk	An analyst's *ESGTalk* minus the median *ESGTalk* of all analysts participating in the same earnings conference call, where positive values indicate above-median ESG engagement relative to call peers.
Analyst_HasESG	An indicator variable equal to one if an analyst uses ESG words-or-phrases during a call, and zero otherwise.
Call_HasESG	An indicator variable equal to one if any analyst uses ESG words-or-phrases during the call, and zero otherwise.
Control variables	
Size	Total asset of a firm in year *t*.
ROA	Return on asset of a firm in year *t*, calculated as net income before extraordinary items divided by beginning-of-year total assets.
Leverage	The leverage ratio of a firm in year *t*, calculated as the sum of current and long-term debts scaled by stockholders' equity.
BTM	The book-to-market ratio of a firm in year *t*, calculated as stockholders' equity divided by market capitalization.
Volume	The natural logarithm of trading volume of a firm in year *t*.
Earnings Surprise	The absolute difference between actual earnings and the most recent median analyst consensus forecast prior to the earnings announcement, scaled by stock price, and is ranked into deciles by year.

Appendix B. Timeline of State-Level Anti-ESG Bills

This table lists U.S. states that have introduced anti-ESG legislation during 2021–2024, along with the year of introduction of the bill, the classification of the bill, and a brief description. Anti-ESG bills are categorized following common typologies used in policy analyses: (1) Pecuniary bills restrict the consideration of ESG factors in investment decisions for public funds (e.g., pension investment constraints, investment-contract restrictions); (2) Boycott bills prohibit state agencies from contracting with or investing in firms perceived to "boycott" certain industries (typically fossil fuels); and (3) Discrimination bills prohibit state agencies, state-run pension systems, and other public entities from using ESG-related or social-credit scoring systems in evaluating firms or individuals. The descriptions summarize the major provisions of each bill. Data on anti-ESG bills are compiled from publicly available legislative records, including state legislatures' bill-tracking systems and cross-verified with third-party policy databases such as the Pleiades Strategy Live Anti-ESG State Action Tracker and the LegiScan database, last accessed August 8, 2024.

N	State	Year	Category	Description of the Bills
1	Arkansas	2023	Pecuniary	Arkansas HB 1253. Restricted Pension Investments.
2	Florida	2023	Pecuniary	Florida H 0003. Government ESG Score Ban, Restricted Pension Investments, Restricted Investment Contracts, Proxy Shareholder Voting Restrictions.
3	Georgia	2023	Pecuniary	Georgia HB 481. Restricted Pension Investments, Proxy Shareholder Voting Restrictions.
4	Idaho	2023	Boycott	Idaho H 0190. Restricted Investment Contracts.
5	Indiana	2023	Pecuniary	Indiana HB 1008. Restricted Pension Investments, Proxy Shareholder Voting Restrictions.
6	Kansas	2023	Pecuniary	Kansas HB 2100. Restricted Pension Investments, Proxy Shareholder Voting Restrictions.
7	Kentucky	2023	Pecuniary	Kentucky HB 236. Restricted Pension Investments, Proxy Shareholder Voting Restrictions.
8	Louisiana	2024	Discrimination	Louisiana SB 234. Restricted Investment Contracts.
9	Montana	2023	Pecuniary	Montana HB 228. Restricted Pension Investments, Proxy Shareholder Voting Restrictions.
10	New Hampshire	2023	Discrimination	New Hampshire HB 457. Restricted Pension Investment.
11	North Carolina	2023	Pecuniary	North Carolina H 750. Restricted Pension Investments, Government ESG Score Ban.
12	North Dakota	2021	Boycott	North Dakota HB 1164. Opposing Federal Rules.
13	Oklahoma	2021	Pecuniary	Oklahoma HB 1236. Opposing Federal Rules.
14	South Carolina	2023	Pecuniary	South Carolina H 3690. Restricted Pension Investments, Proxy Shareholder Voting Restrictions.
15	Tennessee	2024	Discrimination	Tennessee HB 2100. Chilling Effect (Civil Liability).
16	Texas	2021	Pecuniary, Boycott	Texas SB 13. Restricted Investment Contracts, Restricted Pension Investments.
17	Utah	2023	Discrimination	Utah HB 281. Government ESG Score Ban.
18	West Virginia	2023	Pecuniary	West Virginia HB 2862. Restricted Pension Investments, Proxy Shareholder Voting Restrictions.
19	Wyoming	2021	Discrimination	Wyoming HB 0236. Private Sector ESG Score Ban.

Appendix C. Qualitative Evidence of ESG Orientation

As a qualitative validation of our ESG orientation classification, we examine information available about analysts online, including their LinkedIn profiles and other public information, for evidence of an ESG orientation. We randomly select 50 ESG-oriented analysts and 50 non-ESG-oriented analysts based on our classification, and examine those analysts. For all selected analysts, we locate their LinkedIn profiles and conduct a search for other publicly available professional information available online. A variety of search tools are used, including AI-assisted tools, and all information is verified using primary sources (LinkedIn page, corporate webpage, conference call transcripts, conference programs and transcripts, etc.). Analysts' names were provided to research assistants in mixed batches, in alphabetical order within batches, so that there was no indication of ESG orientation expectations. Research assistants were instructed to stop searching if clear indication of ESG- or anti-ESG orientation was found, or if 20 minutes of effective/ productive search was completed, whichever occurred first. While this search is not exhaustive, and ESG orientation is inherently subjective, this search allows us to provide additional qualitative evidence on visible signals of ESG orientation. Panel A summarizes the number of analysts for which ESG-orientation evidence was found. The narrow criteria exclusively counts analysts demonstrating individual/personal alignment with an ESG perspective while working as an analyst. The broad criteria additionally includes analysts who are employed at firms with clear ESG focus and analysts who demonstrate ESG focus in their post-analyst work choices (e.g., choosing to work as an Investor Relations professional at an ESG-focused company). Panel B provides specific examples of the types of evidence found to indicate ESG focus.

Panel A. Summary of Qualitative ESG-Orientation Validation Evidence

	Number of Analysts Examined	Evidence of ESG orientation: Narrow criteria		Evidence of ESG orientation: Broad criteria	
		Number	%	Number	%
ESG-oriented Analysts	50	13	26%	22	44%
Non-ESG-oriented Analysts	50	5	10%	9	18%

Panel B. Examples of Evidence

Type of Evidence	Example(s)
ESG-focused question(s) on conference calls.	"Now, you're talking about ramping up the greenhouse gas reduction goals, right, through that period, through 2025 and 2030. Does that increase that asset growth rate at all during that period? And also, does that mean that you might be at the higher end of our EPS growth range as well?" "First question, your European and Canadian peers have all committed to a net zero target. Chevron still has not done so here so I'm wondering what you see as the gating items that would need to happen to commit to a net zero target." "Hey, just a follow-up on ESG. Just any thoughts as to the restructuring of how that relates to agreeable business as part of the restructuring and how it's going to impact the rest of Moody's?"
ESG-related skills/training/content posted on LinkedIn	Lists certificate for "Sustainable Real Estate: Creating a Better Built Environment" on LinkedIn page. Lists "Sustainability" as a skill on LinkedIn page. Leads the equity research team for utilities and alternative energy; professional profile emphasizes alternative energy expertise.

Type of Evidence	Example(s)
ESG-focused coverage choices, presentations	Coverage focused on companies with significant business in sustainable materials, alternative energy, and/or the circular economy. Featured as an "expert voice" on the transition to recyclable materials during the 18th Annual Farm to Market Conference. Quote from conference transcript: "So 35% of the U.S. food supply chain is wasted, which is clearly unfortunate and disturbing given that one in eight Americans struggle with hunger. So this is a very big topic for our food retail coverage, both from an ESG standpoint, but also for an efficiency and cost savings standpoint. And so the good news is that the companies and stakeholders are very aligned on this topic"
ESG-focused content in reports/report sections/notes	Authored ESG-focused research notes such as "ESG Research Takeaways From Asset Managers' ESG Panel." Report content: "We are refreshing our ESG view on the E-Commerce Sector. We first highlight the Sustainability Accounting Standards Board's view & then present our view on the top three, updated and narrowed from five, issues and why: 1) Employee Engagement, Diversity & Inclusion 2) GHG Emissions; and 3) Customer Privacy. We then explore ESG opps [opportunities]."
Clear ESG focus at the brokerage house or research firm that employs the given analyst. (Included only in broad criteria.)	Bank of Montreal (BMO)'s ESG policy: "We integrate sustainability across our business and help clients and communities achieve their sustainability and risk management goals." Piper Sandler ESG policy: "We provide equity research insights to help investors evaluate ESG-related performance and allow them to make the most informed investment decisions."
Post-analyst position in investor relations (IR), with clear ESG content/focus in IR role. (Included only in broad criteria.)	ESG Report prepared by given analyst in post-analyst role: "Prepared within the Global Reporting Initiative (GRI) Standards Framework, the 2021 Diebold Nixdorf ESG report highlights the strides the company made throughout the year in environmental stewardship, global citizenship and corporate governance." Sustainability Report prepared by given analyst in post-analyst role: "Our sustainability strategy is built on the pillars of environmental commitment, social responsibility and ethical governance. Our sustainability initiatives are backed by a strong governance structure that encourages accountability and fosters ongoing progress on sustainability issues." ESG/Sustainability Report prepared by given analyst in post-analyst role: "Our company was founded with the belief that existing for more than profit matters. In our ESG report, we outline how this principle shapes our commitments and continues to move our business forward."