Does media coverage of firms' environment, social, and governance (ESG) incidents affect analyst coverage and forecasts? A risk perspective⋆

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Abstract: We examine whether and how media coverage of firms' environment, social, and governance (ESG) incidents is associated with analyst coverage and forecasts. We propound that the risks of firms could either increase or decrease as a result of media-covered ESG incidents, depending on the firms' actions on the media coverage, and thus its impact on analyst coverage and forecasts would vary. Based on a sample of U.S. listed companies, we find evidence that the level of analyst coverage is negatively associated with a firm's ESG incidents covered by the media. This association is more pronounced for firms with more intense industrial product market competition, more severe ESG scandals, or coverage by less sophisticated analysts. We also find that the firms' ESG incidents covered by the media would lead to higher levels of forecast error and dispersion. Our mediation analysis further reveals that business risk and information risk tend to be higher for firms covered by the media for having been involved in ESG incidents, thereby explaining why the analysts' coverage and forecasts for these firms are adversely affected. Overall, our results highlight the importance of curbing corporate social irresponsibility and improving analyst performance in forecasting.

Keywords: corporate social irresponsibility; media coverage; analyst following; analyst forecast error; analyst forecast dispersion

JEL classification codes: G14; M14; M41

1. Introduction

The strong emphasis on sustainability and ethics worldwide has led to increased attention to the companies' role as social citizens. Against this backdrop, researchers have intensively explored issues regarding corporate social responsibility (CSR). However, a paucity of research investigates corporate social irresponsibility (CSI) and its economic ramifications that differ substantially from those of CSR (e.g., He et al., 2023). To complement the literature, we focus on media coverage of negative environmental, social, and governance (ESG) issues, and examine its impact on analyst forecast behaviors in the United States. Analysts play an important role as information intermediaries in the stock market by helping investors better understand a firm's risk, performance, and future prospect. Hence, the analysts' responses to media coverage of negative ESG incidents are of great significance for understanding the market consequences of CSI.

Media coverage of ESG incidents brings reputational losses and legal fines to a firm (Karpoff et al., 2008; Philippe & Durand, 2011; Lin et al., 2016).[1] In consequence, its stakeholders become less willing, and even antipathetic, to maintain a business relationship with the firm. This increases the uncertainty of the firm's operational activities and future performance. To mitigate the reputational losses and threat of litigation, managers might implement strategic changes, which add further uncertainty to future firm performance, or withhold other potential corporate bad news, thereby leading to high information risk for the firm.[2] The uncertain future performance and the opaque information environment increase the difficulty and costs for analysts to provide accurate earnings forecasts. Furthermore, as a firm subject to media coverage of ESG incidents is likely to

[1] All through the paper, the media-covered ESG incidents are referred to as those reflective of negative ESG issues with a firm.

[2] As with previous research (e.g., Bhattacharya et al., 2012; Lambert et al., 2012), information risk is defined as the risk of the information users making bad judgement and decision-making due to high information opacity of firms.

be less attractive for investments by investors, they will have lower demand for analyst services, thereby making it less beneficial for analysts to forecast earnings for the firm. To the extent that business risk and information risk are higher for firms with media-covered ESG incidents, analyst forecast error and dispersion would be larger for these firms.

In another scenario, firms covered by the media for their ESG incidents might seek to restore their reputation by promptly implementing effective control over ESG risks and increasing their information transparency to stakeholders. As such, information risk and business risk would be mitigated, plausibly leading to higher analyst following, lower analyst-forecast error, and lower forecast dispersion, given that analysts incorporate latest news into their coverage and forecasts for the firms. On balance, whether and how media coverage of ESG incidents affects analyst coverage and forecasts is an open question that warrants empirical analysis.

We use the RepRisk Index from the RepRisk database to construct a measure of media coverage of ESG incidents, which captures the reach, severity, novelty, and intensity of the firms' ESG incidents covered by the media. Based on a sample of U.S. listed companies, we find that analyst coverage is negatively associated with media coverage of ESG incidents. This finding is robust to using a test of impact threshold for a confounding variable (ITCV), an Oster (2019) test for coefficient stability, a two-stage least squares (2SLS) regression, two falsification tests (and a Heckman two-stage regression) to control for potential endogeneity (and sample selection bias). The association is stronger for firms that face more fierce industrial product market competition, more severe ESG incidents, and higher coverage by less-sophisticated analysts. Furthermore, we find that media coverage of ESG incidents increases forecast error and forecast dispersion of analysts. This finding is both statistically and economically significant and is also amenable to employing the ITCV test, Oster (2019) test for coefficient stability, 2SLS regression (and Heckman two-stage regression) to mitigate potential endogeneity (and sample selection bias). The analyst coverage and forecasts are about a firm's earnings rather than CSI, so they are unlikely to reversely affect the media coverage which concerns the ESG incidents. Or rather, when deciding on whether and how to cover negative ESG incidents of a firm, the media normally would not refer to analyst coverage of the firm's earnings. Therefore, our analysis should, by nature, be subject little to reverse causality issues. Our robustness checks for endogeneity are consistent with this notion. In addition, we find evidence to suggest that increased corporate risk and uncertainty are the underlying mechanisms through which media-covered ESG incidents reduce analyst coverage and increase forecast error and dispersion.

Our paper contributes to the literature in the following ways. First is the contribution to the literature on financial analysts. There is extensive evidence (e.g., Lang & Lundholm, 1996; Barth et al., 2001; Simpson, 2010; Dhaliwal et al., 2012; He et al., 2019a) on how analyst behavior is shaped by various financial or non-financial information disclosed by managers. Yet, little research sheds light on how analysts react to value-relevant information provided by third parties such as the media.[3] We fill this gap in the literature. Furthermore, our study takes a new risk perspective and illustrates how analysts' judgment and decision-making are shaped by an information disclosure via its risk impact on firms. In particular, we propound that the risk impact depends on the firms' actions on the media coverage and could either be positive or negative from a theoretical point of view. Our results for mediation tests reveal that the business risk and information risk of a firm would increase as a result of media coverage of ESG incidents, thereby

[3] Bradshaw et al. (2021) examine how analysts revise their earnings forecasts in response to the soft information covered by the media. Our paper differs from Bradshaw et al. in three aspects. First, we look at a specific type of media-covered information, CSI, rather than soft information. Second, we probe analyst coverage and forecast properties other than the forecast revisions made by analysts. Third, when investigating the influence of media-covered CSI on analysts' forecasting behavior, we focus on analyzing the economic consequences of media coverage on firms.

deter analysts from following the firm, and increase their forecast error and dispersion.

Second, we also add to the literature which holds mixed views and evidence on analyst sophistication (Chandra et al., 1999; Rajgopal et al., 2003; Kothari et al., 2016; Rahman et al., 2019; He et al., 2019a). As the economic consequences that media coverage of CSI would have on firms are highly uncertain by nature, whether analysts are sophisticated enough to properly process the information about the media-covered CSI is an open question that warrants an empirical analysis. Our findings suggest that analysts lack such sophistication.

Third, we complement the scarce research on the market consequences of CSI by examining how media coverage of ESG incidents affects the coverage and forecasts by analysts who play the role of information intermediaries for investors in the stock market. Analysts are presumably more sophisticated in the U.S. stock market than in other less developed stock markets. Still, we find that in the U.S. market, such media coverage of CSI undermines the analysts' information intermediary role in terms of reduced analyst coverage, increased forecast error, and enlarged forecast dispersion. These findings underscore the importance of curbing CSI and improving analyst performance in forecasting.

The remainder of this paper is arranged as follows: Section 2 reviews the related literature and develops our hypotheses. Section 3 describes the data sources, sample, and measurement of main variables. Section 4 presents our research design and discusses the empirical results. Section 5 concludes.

2. Literature Review and Hypothesis Development

2.1 Research background

Environmental, social, and governance (ESG) incidents, which are three dominating concerns over CSI, impair the public's trust in the offending firms and adversely impact their operation and financial stability. ESG scandals such as the Deepwater Horizon oil spill disaster in 2001, the Rana Plaza collapse in 2013, the Volkswagen emissions scandal in 2015, and the Facebook-Cambridge Analytical data scandal in 2018 evoked fierce protests from customers and other stakeholders, caused a huge number of legal fines and reputational losses to the firms, and thereby harmed the firms' performance and the shareholders' interests. These events highlight the importance of understanding CSI and its market consequences. To this end, we focus on exploring media coverage of ESG incidents for three reasons.

First, unlike information about CSR which is often self-disclosed originally by firms, CSI-related information is commonly covered by the media. Managers tend to withhold bad news (e.g., Kothari et al., 2009), making it less likely for a firm to self-disclose its ESG incidents. Stakeholders will not respond to any ESG incident if they are unaware of it (Barnett, 2014). Therefore, the economic consequences of CSI to a firm depend crucially on how well CSI is known to widespread stakeholders. The media can serve this end well by revealing and disseminating CSI-related information to a wide variety of stakeholders (e.g., He et al., 2024).

Second, humans are usually more attentive to negative rather than positive information (Rozin & Royzman, 2001), especially when the information is associated with their own interests. This information preference not only creates an incentive for stakeholders to underscore any CSI issue that harms their own interests (Barnett, 2014; Kölbel et al., 2017), but also gives the media a high motive to report ESG scandals to cater to the information needs of stakeholders. Covering negative ESG issues helps the media increase the number of views, subscriptions, and thus revenues to a substantial extent.

Third, a firm that engages actively in CSR activities can be socially irresponsible in some respects (e.g., Kang et al., 2016; Lenz et al., 2017; Oikonomou et al., 2014; Chen et al., 2020; Raghunandan & Rajgopal, 2022). So CSI and CSR may co-exist in a firm. Media coverage of ESG incidents purges CSI out of CSR, and is a relatively clean measure of the former, and thus the focus of our study for shedding light on the stock market consequences of CSI through exploring its impact on the coverage and forecasts by analysts who play the role as information intermediaries in the stock market.

2.2 The potential risk impact of media coverage of ESG incidents

The risks of a firm reflect the uncertainty of its future performance and should impact analysts' performance in their coverage and forecasts for firms. It is thus important to understand the risk impact of media coverage of ESG incidents. It may influence firm risks in the following ways. First, ESG scandals tarnish a firm's reputation and impair stakeholders' trust in the firm. Economic theory (Klein & Leffler, 1981; Shapiro, 1983) emphasizes the importance of trust and reputational capital as a foundation for doing business with customers, suppliers, investors, employees, and other stakeholders. Good reputation helps a firm produce favorable terms of contracts with stakeholders, whereas bad reputation deteriorates a firm's business relationship with stakeholders and disrupts its operating and financing activities (e.g., Fombrun & Shanley, 1990; Fombrun, 1996; Hansen et al., 2011; Cao et al., 2015; Li et al., 2024). Stakeholders losing trust in a firm involved in ESG incidents would be reluctant to do business with, and even pose sanctions on, the firm (Sweetin et al., 2013). For instance, consumers might boycott products of an unethical, socially irresponsible firm and even spread negative word-of-mouth to a range of acquaintances, causing instability of future sales to the firm (Mohr & Webb, 2005; Braunsberger & Buckler, 2011; Lindenmeier et al., 2012; Grappi et al., 2013). Put generally, the reputational losses attributed to

CSI might provoke an array of unfavorable business reactions from various stakeholders; this would increase the business risk of the firm and make its future performance less predictable.

Second, ESG incidents covered by the media might bring about potential litigation costs, regulatory fines, and other costs, which are often uncertain in terms of the actual amount to incur. For example, the British Petroleum company had paid around $64 billion by September 2018 to cover environmental clean-up, compensation, and penalties for the Deepwater Horizon oil spill in the year 2010. As lawsuits resulting from the oil spill event took a long time to settle, British Petroleum's commitment to paying environmental clean-up fees, fines, and other relevant fees is uncertain, hence adding uncertainty to the firm's future performance.

Third, media coverage of ESG incidents might trigger strategic changes by a firm, making its future prospect uncertain. As the media uncovers and broadcasts negative ESG information to a widespread audience, criticism and stigmatization from the public will run against the firm, resulting in the loss of its reputation (Wiesenfeld et al., 2008). To recoup the reputational losses and allay the threat of litigation, the firm might have an incentive to change its business strategies in response to the negative media coverage. In line with this argument, Bednar et al. (2013) provide a positive association between negative media coverage and strategic changes, based on a longitudinal analysis of 250 U.S. companies. The strategic changes by the firm, which are made in response to the media exposures of ESG incidents rather than increase its competitive advantage, might lead to uncertain firm performance.

Besides, a firm of which ESG incidents are broadcasted by the media may withhold other corporate bad news to prevent corporate reputation from deteriorating and to mitigate potential negative consequences of media-covered CSI. This misbehavior increases the information opacity of the firm. In sum, media coverage of ESG incidents might cause high business risk and high information risk to firms.

2.3 The impact of media coverage of ESG incidents on analyst coverage and forecasts

Theory (Bhushan, 1989) and empirical studies (e.g., Lang & Lundholm, 1996; Frankel et al., 2006) both suggest that analyst coverage is driven by the supply of, and demand for, analyst services. In specific, the greater the difficulty in making accurate forecasts for a firm, the lower the supply of analyst services, resulting in lower analysts' coverage on the firm. Meanwhile, lower investors' demand for analyst services would also lead to lower analyst coverage. Accordingly, we take both the supply- and demand-curve perspectives to establish a theoretical link between media-covered ESG incidents and analyst coverage. On the one hand, the high business risk and high information risk plausibly caused by media coverage of ESG incidents would make it difficult for analysts to provide accurate forecasts. This demotivates analysts to cover firms that have media-covered ESG incidents. On the other hand, investors' demand for analyst services determines the benefits analysts can obtain from covering a firm (Bhushan, 1989). Investors might have less interest in investments in stocks of a firm that is subject to media coverage of ESG incidents and associated reputational losses, as these stocks tend to have higher risks and lower returns (Cox et al., 2004; Johnson & Greening, 1999; Wong & Zhang, 2022; Rojo-Suarez & Alonso-Conde, 2024). This inference is more evident for institutional investors who are often under social pressure that deters them from investing in a socially irresponsible firm (Ryan & Schneider, 2002). Because of the lower investor demand for analysts covering a socially irresponsible firm, it will be less beneficial for analysts to cover such a firm.

Nonetheless, in another scenario, firms covered by the media for their ESG incidents might promptly take effective measures to contain ESG risks. With improvements in the risk management, the stakeholders' trust and confidence in the firms might be restored. Meanwhile, the firms might also actively disclose the associated ESG information, among others, to show credibility and transparency for the stakeholders. In such a scenario, with the revelation of ESG incidents that are previously unknown or known less, the business risk and information risk of the firms would not increase and might become even lower, reducing the difficulty for analysts to make accurate forecasts. Investors might still have an interest in investing in the firms that learn from the ESG incidents and make an effort to improve their ESG performance. Based on the above discussion from the two opposing perspectives, we make the following non-directional hypothesis for empirical analysis:

H1: Analyst coverage is associated with media coverage of ESG incidents.

Analysts are supposed to refer to updated risk-related information for their coverage and forecasts. Provided that firms with ESG incidents covered by the media, as discussed previously, have higher (lower) levels of business risk and information risk, it will be relatively more (less) difficult for analysts to make accurate forecasts for such firms. Given the two opposing possibilities, we propose the following non-directional hypothesis:

H2: Analyst forecast error is associated with media coverage of ESG incidents.

Apart from analyst forecast error, forecast dispersion may also be influenced by media coverage of CSI. It is noteworthy that an increase (or decrease) in analyst forecast error does not necessarily denote an increase (or decrease) in forecast dispersion, since changes in forecast error in the same direction and to the same degree among different analysts would denote no forecast dispersion. We expect that the plausible increase (decrease) in the information risk and business risk due to media coverage of ESG incidents would increase (decrease) the variance in forecast inputs and parameters used by different analysts, thereby enlarging (reducing) the divergence in their forecasts.

Analysts differ in sophistication, knowledge, and professionalism (Fang & Yasuda, 2014). Previous studies (Hunton & McEwen, 1997; Sidhu & Tan, 2011) suggest that more experienced, knowledgeable, and skillful analysts are more adept at gathering and processing value-relevant information and are thus more able to provide accurate forecasts. In the case of high business risk and information risk for the firms, more able analysts should maintain forecast accuracy better than others, thus causing an increased dispersion in analysts' forecasts. On the contrary, if the business risk and information risk are low, it would be relatively easier for all analysts to maintain forecast accuracy. In consequence, the forecast dispersion would be lower.

Furthermore, different analysts may hold different sets of value-relevant information or put different weights on diverse information used in forecasting (Lang & Lundholm, 1996). For example, analysts hired by large stock-brokerage firms enjoy stronger research support and resources, better relationships with companies, and thus superior access to information (Jacob et al., 1999). In a plausibly opaque information environment of a firm subject to media coverage of ESG incidents, the difference in access to information is likely to induce various opinions formed by different analysts; even if there is no significant difference in the information collected, analysts may put different weights on the varied information used for forecasting, with subjective judgments involved in this process. As a result, analyst forecasts might diverge to a substantive extent. The divergence might also increase when analysts use different forecasting models. Conversely, the analysts' forecasts would likely converge if the firm's information is more transparent. In light of the above discussion in relation to the opposing arguments made previously for the hypothesis H1, we put forward our third hypothesis in a non-directional form as follows:

H3: Analyst forecast dispersion is associated with media coverage of ESG incidents.

3. Data

Our empirical analysis is conducted based on a sample of U.S. listed companies, with data obtained from the RepRisk, Institutional Brokers Estimate Systems (I/B/E/S), Factset, Center for Research in Security Prices (CRSP), and Compustat databases. Data on ESG incidents are gathered from RepRisk, which is an ESG data science company based in Zurich. Data on analyst coverage and forecasts are collected from I/B/E/S. Data on institutional stock ownership are gathered from Factset. Other data are taken from CRSP and Compustat. Our sample period ranges from 2007 to 2015.[4] We require that all firm-year observations have the necessary data required to construct variables of interest for our regression analyses. This gives us 3,097 firm-year observations for 992 unique firms for our empirical tests.

Media coverage of ESG incidents is measured by the RepRisk Index (RRI) constructed by RepRisk. It dynamically tracks 28 types of ESG incidents (see Appendix 1) from a wide range of media and associated public sources. The RRI index is constructed based on news value and news intensity (RepRisk, 2018). News value is within the range of 0-52 and measured by the product of the time-weighted averages of the reach of information sources, the severity of incidents and criticism, and the novelty of issues in the last two years. The news intensity ranges from 1 to 3, hinging on the frequency of incidents in the last two months. Appendix 2 shows the proprietary algorithm of the RRI index. It is calculated on a monthly basis and ranges from 0 to 100. A higher RRI score indicates greater problems with a firm's ESG incidents covered by the media. RRI is recalculated when there is new news about a firm, and decays to 0 over a maximum period of two years if no new criticism is captured.

[4] In an un-tabulated analysis, we exclude the financial crisis period of 2007-2009, and still find a significant and negative (positive) impact of media coverage of ESG incidents on analyst coverage (forecast error and dispersion) in the post-financial crisis period which ranges from 2010 to 2015.

We use the RepRisk data, rather than the MSCI ESG Research (previously known as KLD) data, for two reasons. First, the MSCI database includes firms' self-reported CSR information. The self-reporting leaves much latitude for a firm to manipulate its ESG ratings as it wishes (e.g., Pinnuck et al., 2021; Chen et al., 2023). By contrast, RepRisk systematically searches through over 80,000 media together with other related external information sources, from which the information about ESG incidents is relatively more reliable and objective than the one self-reported by a firm. Second, MSCI puts the same weight on each ESG concern without regard to the different severity among different ESG issues. On the contrary, RepRisk distinguishes major ESG incidents from minor ones by quantifying the reach, severity, novelty, and intensity of ESG incidents. Since RRI scores pertain to monthly data, we construct a variable *avg_rri_std*, which is the average monthly RRI scores in a fiscal year, scaled by the standard deviation of the monthly RRI scores, to measure media coverage of CSI.[5] A higher value of *avg_rri_std* represents a greater level of problems with ESG incidents covered by the media.

4. Research Design and Results

4.1 Multivariate Test of the Hypothesis H1

4.1.1 Baseline Regression Analysis

To test whether media coverage of ESG incidents is negatively or positively associated with

[5] We scale the average monthly RRI scores by the standard deviation to account for the variance effect of monthly CSI, in addition to the mean effect. Such scaling is consistent with the construction of the t-statistic that is scaled by standard error, and also applies to the measure of post-earnings-announcement drift, for which the variable is scaled by the standard deviation of earnings surprises (e.g., Bernard & Thomas, 1989; Mendenhall, 2004; Sadka, 2006; Feldman et al., 2010; He, 2021). For robustness check, we use the average monthly RRI scores for a year (namely, *avg_rri*), which are not scaled by the standard deviation of monthly RRI scores, as the alternative key independent variable for our baseline regression analyses. The results, not tabulated for simplicity, indicate a statistically significant negative (positive) association between media coverage of ESG issues and analyst coverage (forecast error and dispersion). In addition, the maximum monthly RRI score in a year is not used as our measure of media-covered CSI, because this measure is likely to be subject to outlier problems from the statistical perspective.

analyst coverage, we employ the following ordinary least squares (OLS) regression model:

$$lnanacov_{t+1,i} = \alpha_0 + \alpha_1 avg\_rri\_std_{t,i} + \alpha_2 size_{t,i} + \alpha_3 idiosynretvol_{t,i} + \alpha_4 price_{t,i} + \alpha_5 qtrret_{t,i} \\ + \alpha_6 roa_{t,i} + \alpha_7 finconstraint_{t,i} + \alpha_8 r\&d_{t,i} + \alpha_9 intangible_{t,i} + \alpha_{10} btm_{t,i} + \alpha_{11} insti_{t,i} \\ + \alpha_{12} tradingvol_{t,i} + \alpha_{13} regulated_{t,i} + \alpha_{14} yeardum + \alpha_{15} industrydum + \varepsilon_{t+1,i} \quad (1)$$

where *lnanacov* equals the natural logarithm of one plus the number of analysts that make at least one annual earnings per share (EPS) forecast for a firm at fiscal year t+1. If there is no analyst forecasting annual EPS at the fiscal year, *lnanacov* takes the value of zero (e.g., Lehavy et al., 2011; He et al., 2019b; Zhang & Wu, 2023). The key independent variable *avg_rri_std* and the control variables are measured at fiscal year t. The standard errors of coefficients are clustered at the firm level for all our regression analyses in this study.

Model (1) incorporates a host of control variables that are found by previous research to be correlated with analyst coverage. These variables include firm size (*size*) (e.g., Bhushan, 1989), idiosyncratic return volatility (*idiosynretvol*) (e.g., Bhushan, 1989), abnormal stock returns (*qtrret*) (e.g., Brennan & Hughes, 1991; Siconolfi, 1995), share price (*price*) (e.g., Brennan & Hughes, 1991), return on assets (*roa*), financial constraints (*finconstraint*) (e.g., Das et al., 2006; Lee & So, 2017), R&D expenses (*r&d*) (e.g., He et al., 2020), intangible assets (*intangible*) (e.g., Barth et al. 2001), the book-to-market ratio (*btm*) (e.g., Aboody & Lev, 2000; Lev, 2001; Huddart & Ke, 2007), institutional stock ownership (*insti*) (e.g., Bhushan, 1989; O’Brien & Bhushan, 1990), trading volume (*tradingvol*) (e.g., Frankel et al., 2006), and industrial regulatory status (*regulated*) (e.g., O’Brien & Bhushan, 1990). The variable definitions are given in Appendix 3. In addition, as shown in Table 1, both analyst coverage (*lnanacov*) and media-covered CSI (*avg_rri_std*) vary substantially across industries and years, consistent with the related literature (e.g., Lehavy et al., 2011; Kölbel et al., 2017). Therefore, we also include industry dummies (*industrydum*) and year dummies (*yeardum*) in Model (1). We do not control for firm-fixed effects in the regression as they are multicollinear with industry dummies.[6]

Table 2 reports descriptive statistics of *avg_rri_std* as well as other variables used in our multivariate tests. All the continuous variables with outliers are winsorized at 1 and 99 percentage points, respectively.[7] Table 3 reports the regression results for the hypothesis H1. The coefficient on *avg_rri_std* is negative and statistically significant at the 1% level, indicating that analyst coverage is negatively associated with media coverage of ESG incidents.[8] A one-standard-deviation increase in *avg_rri_std* induces a decrease in *lnanacov* by 4.19% of its one standard deviation. The majority of the control variables are statistically significant in the predicted direction. Results of our variance inflation factor (VIF) tests, not tabulated for the sake of brevity, indicate that the VIF values of all continuous variables, except for *size* of which the VIF value is 6.57, are below 4, suggesting that our regression model is free from multicollinearity issues.

4.1.2 Control for Endogeneity

To mitigate potential correlated-omitted-variable(s) bias, we control for a battery of variables along with industry- and year-fixed effects in Model (1). However, it is still plausible that analyst coverage and media-covered ESG incidents are driven by unobservable omitted variable(s). To assuage this concern, we follow previous research (e.g., Frank, 2000; Larcker & Rusticus, 2010) to analyze the impact threshold for a confounding variable (ITCV) for our baseline multivariate

[6] Furthermore, the firm-fixed-effects regression assumes that both the dependent variable and independent variable have sufficient time-variance. However, media coverage of ESG incidents and analyst coverage are relatively sticky in the time-series. It is thus not suitable to include firm-fixed effects in our baseline regression.
[7] The variables that have outliers and are thus winsorized include *price*, *qtrret*, *finconstraint*, *idiosynretvol*, *btm*, *error*, *optimism*, *pessimism*, and *dispersion*. In addition, we exclude observations with no or little analyst coverage by trimming our full sample at the bottom 5% of the distribution of the variable. Using this sample for the regression analysis, we obtain qualitatively the same results.
[8] As the analyst coverage variable *per se* is not subject to censorship problems, there is no need to run a Tobit regression for Model (1). That said, running a Tobit regression which sets the left-censoring point to 0 for *lnanacov*, we obtain qualitatively the same result – that the coefficient of *avg_rri_std* is negative and statistically significant at the 1% level.

tests. The ITCV analysis identifies a single-valued threshold beyond which our results and inferences on the key independent variable would be overturned. The larger the value of ITCV, the less likely our regression results are subject to potential correlated-omitted-variable(s) bias. Table 4 presents the results of the ITCV test for the baseline regression analysis. The estimated absolute value of ITCV is 0.0186, which is higher than any absolute value of the impact factor (*Impact*) of variables (except for *size*) controlled in Model (1). As firm size is a fundamental determinant of both analyst coverage and ESG risk exposures, it is not surprising that the absolute value of the impact factor of firm size is larger than that of ITCV and other control variables. We may rest assured that our baseline regression results are reasonably amenable to accounting for the potential correlated-omitted variable(s).

We also employ the Oster identified sets to assess the stability of our baseline results against potential correlated-omitted-variable(s) bias or measurement errors. Using the R-squares and the coefficients of the key independent variable of interest from the regressions with and without control variables, Oster (2019) creates identifiable sets. If zero is not included in the identifiable sets, the regression results are unlikely to be biased by correlated omitted variable(s). Table 5 displays the results of the Oster identified sets under three assumptions proposed by Oster (2019). None of our identified sets that cover the ranges [-0.0350, -0.0122], [-0.0579, -0.0122], and [-0.0640, -0.0122] include zero. These results indicate that our baseline regression results are unlikely to be plagued by correlated-omitted-variable(s) bias or measurement errors.

The decision of the media to cover negative ESG incidents of a firm is unlikely to be driven by analyst coverage and forecasts that relate to a firm's projected earnings performance rather than CSI itself. Therefore, reverse causality is arguably less of a concern in our study. Still, we perform a two-stage least-squares (2SLS) regression analysis to substantiate this notion. Some industries are inherently exposed to higher ESG risk than others, so firms in these industries are more likely to perpetrate CSI. Yet, the industry-level ESG-risk exposure is unlikely to directly affect an analyst's decision on whether to cover a firm. Therefore, we include the industrial ESG-risk exposure (*esg_risks_industry*) as the instrumental variable for our 2SLS regression analysis. Besides, as the calculation of RRI accounts for the value and intensity of news, we believe that either the industry-level or firm-specific news count on ESG issues (namely, *lyr_esg* and *lyr_esg_industry,* respectively) is related to *avg_rri_std*,[9] but the news count *per se* should have little impact on analyst forecast behavior, except indirectly through *avg_rri_std*. Or rather, given the effects of the media coverage of ESG incidents (*avg_rri_std*) which captures the reach, severity, novelty, and intensity of ESG issues, the news count should barely have a further direct impact on analyst coverage and forecasts; the news count is associated with analyst coverage and forecasts only indirectly through *avg_rri_std* in our 2SLS regression estimation. Thus, the variables for the news count, *lyr_esg* and *lyr_esg_industry*, are also considered as instrumental variables for our regression analysis. All other variables included in the first-stage regression are the same as the control variables used in Model (1), which is run as the second-stage regression.

Table 6 reports the two-stage regression results. Regarding the first-step results, *esg_risks_industry*, *lyr_esg*, and *lyr_esg_industry* have a statistically significant relationship with *avg_rri_std*. A one-standard-deviation increase in *esg_risks_industry* and *lyr_esg* (*lyr_esg_industry*) increase (reduces) *avg_rri_std* significantly by 40.94% and 35.08% (23.70%) of the one-standard-deviation of *avg_rri_std*. A plausible explanation for the negative association between the industry-level news count on ESG issues (*lyr_esg_industry*) and the media-covered CSI (*avg_rri_std*) is that a firm might be cautious about, and self-discipline itself from, pursuing

[9] The Spearman correlation between *avg_rri_std* and *lyr_esg*, not tabulated for parsimony, amounts to 0.5801, suggesting that *avg_rri_std* is not multicollinear with *lyr_esg*.

CSI when many ESG issues are unveiled and broadcasted by the media in the firm's industry. The Cragg-Donald Wald F statistic amounts to 391.357. This figure is far above the cut-off point of 9.08, below which the instrumental variables are considered weak (Stock et al., 2002). Therefore, we can assure that the instruments are strong enough for the 2SLS analysis. In the second-stage regression result, the coefficient on *avg_rri_std* is negative and statistically significant at the 5% level. A one-standard-deviation increase in *avg_rri_std* is associated with a decrease in *lnanacov* by 6.9% of its one standard deviation, which is economically significant. This suggests that our baseline regression results are robust to correcting for the potential reverse causality. The Hansen J statistic is 1.554, indicating that overidentifying restrictions are valid for the 2SLS regression estimation.

To rule out the plausible reverse causality concern, we conduct a falsification test. We run Model (1) respectively on two subsamples that are partitioned by the full-sample median of media-covered CSI (*avg_rri_std*). If the negative relationship runs reversely from high analyst coverage of earnings to low media coverage of ESG incidents, we will find the relation to be more evident in the low-media-covered-CSI subsample. Nonetheless, it is shown from Panel A of Table 7 that the coefficient of *avg_rri_std* is negative and statistically significant at the 5% level for the high-media-covered-CSI subsample but is not statistically significant for the low-media-covered-CSI subsample. This result helps refute the possibility that our baseline results are driven by reverse causality.

Our baseline regression results might also be subject to dynamic endogeneity. In specific, analyst coverage at year t or before might affect media coverage of ESG incidents at year t and thereby influence analyst coverage at year t+1. To exclude this possibility, we conduct another falsification test. Specifically, we run Model (1) based on two subsamples, respectively, which are split by the full-sample median of the time-series variance of *lnanacov* (namely, *stdlnanacov*). If the dynamic endogeneity alternatively explained our baseline regression results, we should find the coefficient of *avg_rri_std* to be significantly more negative in the subsample with higher time-series variance in *lnanacov*. However, as shown in Panel B of Table 7, the coefficient of *avg_rri_std* is negative and statistically significant at the 5% level for the low-variance subsample but is not statistically significant for the high-variance subsample.

We do not adopt a difference-in-differences (DID) regression model to tackle the endogeneity problem for two reasons. First, the DID estimator, in itself, does not capture the heterogeneity of firms' CSI issues in terms of the reach, severity, novelty, and intensity of media-covered CSI incidents. Second, the data on the dates on which CSI incidents were uncovered or broadcasted by the media are not available to us. Hence, we are unable to calculate the change in analyst coverage and forecasts around media coverage of CSI for the DID regression analysis. Even if we could do so, it is almost impossible to conduct a clean DID regression analysis because the media often continually disseminates negative ESG incidents within a certain period. Noticeably, a recent paper by Armstrong et al. (2022) concludes that researchers had better not restrict attention to only those causal issues for which there is DID research design.

In addition, there might be substantial differences in firm characteristics between firms that are subject to media coverage of ESG incidents and those that are not, thereby inducing sample selection bias to our baseline regression results. To alleviate this concern, we perform a Heckman two-stage regression analysis. We construct a binary variable, *ESG_dummy*, to indicate whether a firm is covered by the media for negative ESG issues. Table 8 displays the regression results. In the second-stage results, the coefficient on *avg_rri_std* is negative and statistically significant at the 5% level. This finding suggests that sample selection bias is not a concern in our baseline regression analysis.

4.1.3 Mechanism Tests

As discussed in Section 2, media coverage of ESG incidents affects the business risk and information risk of firms and thereby influences analyst coverage. As such, business risk and information risk mediate the association between media-covered ESG incidents and analyst coverage. High corporate business risk makes it more difficult for analysts to forecast earnings for firms subject to negative media-covered ESG incidents. To provide accurate earnings forecasts for these firms, analysts would have to incur higher information acquisition and/or procession costs for forecasting, and thus they reduce their coverage on the firms. To test the mediating effect of business risk, we employ the following regression models:

$$\begin{aligned} stdearnings_{t,i} = {} & \alpha_0 + \alpha_1 avg\_rri\_std_{t,i} + \alpha_2 size_{t,i} + \alpha_3 salesgrowth_{t,i} + \alpha_4 roa_{t,i} \\ & + \alpha_5 finconstraint_{t,i} + \alpha_6 insti_{t,i} + \alpha_7 yeardum + \alpha_8 industrydum + \varepsilon_{t,i} \end{aligned} \tag{2}$$

$$\begin{aligned} lnanacov_{t+1,i} = {} & \alpha_0 + \alpha_1 pred\_stdearnings_{t,i} + \alpha_2 size_{t,i} + \alpha_3 idiosynretvol_{t,i} + \alpha_4 price_{t,i} \\ & + \alpha_5 qtrret_{t,i} + \alpha_6 ro\alpha_{t,i} + \alpha_7 finconstraint_{t,i} + \alpha_8 r\&d_{t,i} + \alpha_9 intangible_{t,i} \\ & + \alpha_{10} btm_{t,i} + \alpha_{11} insti_{t,i} + \alpha_{12} tradingvol_{t,i} + \alpha_{13} regulated_{t,i} + \alpha_{14} yeardum \\ & + \alpha_{15} industrydum + \varepsilon_{t+1,i} \end{aligned} \tag{3}$$

In line with previous research (e.g., Rountree et al., 2008; Konstantinidi & Pope, 2016), business risk is measured by earnings volatility (*stdearnings*), with a larger value indicating a higher business risk of a firm. Following prior literature (Shleifer & Vishny, 1986; Kraay, 2002; Cowling, 2004; Whited & Wu, 2006; Lee, 2009; Demiralp et al., 2011), we control for a range of determinants of business risk, including firm size (*size*), sales growth (*salesgrowth*), return on assets (*roa*), financial constraints (*finconstraint*), and institutional stock ownership (*insti*). All these variables are defined in Appendix 3.

Previous studies (e.g., Chang et al., 2006) document that analysts are inclined to follow firms with high information transparency, as it is less costly to make a forecast for such firms. In the context of media coverage of ESG issues, high information opacity increases the difficulty in providing an accurate forecast for a firm. Or rather, an opaque information environment not only limits analysts to acquire value-relevant information but also makes it difficult to decipher the value implications of media-covered ESG incidents; it is also hard to detect or monitor any other managerial misconduct that might occur in relation to the ESG issues (Warfield et al., 1995). To maintain forecast accuracy in such a scenario, analysts would have to incur more costs and thus should have a weaker incentive to provide forecasts. To investigate the mediating effect of information risk on the association between media coverage of ESG incidents and analyst coverage, we run the following regression models:

$$bidaskspread_{t,i} = \alpha_0 + \alpha_1 avg\_rri\_std_{t,i} + \alpha_2 size_{t,i} + \alpha_3 salesgrowth_{t,i} + \alpha_4 roa_{t,i} + \alpha_5 insti_{t,i} + \alpha_6 finconstraint_{t,i} + \alpha_7 auditfee_{t,i} + \alpha_8 yeardum + \alpha_9 industrydum + \varepsilon_{t,i} \quad (4)$$

$$lnanacov_{t+1,i} = \alpha_0 + \alpha_1 pred\_bidaskspread_{t,i} + \alpha_2 size_{t,i} + \alpha_3 idiosynretvol_{t,i} + \alpha_4 price_{t,i} + \alpha_5 qtrret_{t,i} + \alpha_6 roa_{t,i} + \alpha_7 finconstraint_{t,i} + \alpha_8 r\&d_{t,i} + \alpha_9 intangible_{t,i} + \alpha_{10} btm_{t,i} + \alpha_{11} insti_{t,i} + \alpha_{12} tradingvol_{t,i} + \alpha_{13} regulated_{t,i} + \alpha_{14} yeardum + \alpha_{15} industrydum + \varepsilon_{t+1,i} \quad (5)$$

As with prior studies (e.g., Muller et al., 2011; Fontes et al., 2018), bid-ask spread (*bidaskspread*) is used as the proxy for a firm's information risk and is estimated by using daily relative effective spreads averaged over a fiscal year. A higher value of *bidaskspread* indicates a higher level of information risk of the firm. In line with previous research (Dechow et al., 1995; Bushee, 1998; Chung et al., 2002; Krishnan, 2003; Ge & McVay, 2005; Ashbaugh-Skaife et al., 2007; Campello et al., 2010), we include in Model (4) a battery of determinants of information risk: firm size (*size*), sales growth (*salesgrowth*), return on assets (*roa*), financial constraints (*finconstraint*), institutional stock ownership (*insti*), and auditing quality (*auditfee*). All of them are defined in Appendix 3.

The mediating effect of business risk (information risk) is captured by the product of the association between media coverage of ESG incidents and business risk (information risk) and the association of the risk with analyst coverage. If the mediating effect exists, the coefficient of *avg_rri_std* in Equation (2) (Equation (4)) should be positive and statistically significant at a conventional level, while the coefficient of *pred_stdearnings* (*pred_bidaskspread*) in Equation (3) (Equation (5)) should be significantly negative. Table 9 shows that the coefficients on *avg_rri_std* and *pred_stdearnings* (*pred_bidaskspread*) are both statistically significant at the conventional level with predicted signs. These results thus corroborate that the increased business risk and increased information risk form the channels through which media coverage of negative ESG issues reduces analyst coverage.

4.1.4 Moderation analyses

We further explore how our baseline regression results vary under different circumstances. When the overall market demand for a certain type of product is substantially lower than those supplied by firms in the industry, the product market will be more competitive. As consumers tend to bear relatively lower costs for switching between suppliers that are in a competitive industry, those suppliers subject to media-covered ESG incidents might face a higher risk of consumer switching and associated higher uncertainty of strategy implementation and sales performance; also, they might have stronger incentives to withhold various other bad news to maintain customers as well as external funders. As such, information risk and business risk would both likely be higher for firms confronting the fierce product market competition and media coverage of ESG incidents. Therefore, it would be more difficult for analysts to cover such firms. This reasoning leads to the supposition that the negative association between analyst coverage and media-covered ESG incidents is more pronounced for firms confronted with intense product market competition.

Material ESG incidents are more value-relevant to firms and have stronger impacts on stock returns, compared to non-material ESG incidents (Khan et al., 2016). On the other hand, the media is inclined to cover material events that have substantial, profound economic consequences on firms, as the material news is likely to attract greater and wider attention from the audience, thereby increasing subscription revenues for the media. Therefore, we expect that media coverage of more severe ESG issues would increase the risk and uncertainty about a firm's future prospect to a larger degree, making it harder for analysts to make accurate earnings forecasts for the firm. As such, the negative association between analyst coverage and media-covered ESG incidents should be more pronounced for firms with more severe ESG incidents.

The costs of acquiring and processing value-relevant information for accurate forecasting, relative to the benefits from the forecasting, would be lower for more-sophisticated analysts. So they are more likely to follow firms with ESG misbehaviors, compared to less-sophisticated analysts. Accordingly, we expect that the negative association between media coverage of ESG issues and analyst coverage is less pronounced for firms covered by more-sophisticated analysts.

To test the foregoing predictions, we divide our full sample into two subsamples based on the median of industrial product market competition, the severity of ESG incidents, and analyst sophistication, respectively, and run Model (1) for each subsample. Karuna (2007) documents three dimensions of industrial product market competition: market size of competing products, product substitutability, and entry costs. Entry costs refer to the minimum investments required of an entrant to join the competition in the industrial product market, and do not represent the intensity of existing product market competition. Thus, we use only the market size (*mktsize*) and substitutability (*substitution*) of competing products to measure industrial product market competition. Both variables are defined in Appendix 3. Larger values of *substitution* and *mktsize* indicate more intense product market competition. Panel A of Table 10 provides the regression results obtained from using *substitution* and *mktsize*, respectively, as the proxies for product market competition. For both proxies, the coefficients of *avg_rri_std* are negative and statistically significant at the 1% level in the high-competition subsamples but not statistically significant at the conventional 5% level in the low-competition subsamples.

The RepRisk database classifies ESG incidents into three categories indicating high, median, and low levels of severity, respectively. To achieve a relative balance in the observations between two subsamples for the moderation analysis, we set the moderator variable *severity* to be 0, if the ESG incidents of a firm are defined by RepRisk as of low severity in a year; otherwise, *severity* is set as 1. The low-severity (high-severity) subsample includes the sample observations that have *severity* equal to 0 (1). Panel B of Table 10 reports the results for the subsample regressions. The coefficient of *avg_rri_std* for the high-severity subsample is negative and statistically significant at the 1% level, whereas the coefficient on *avg_rri_std* for the low-severity subsample is not statistically significant.

Analysts employed by large brokerage houses often have access to more information and more plentiful resources (e.g., Clement, 1999; Jacob et al., 1999), so they are typically more sophisticated than those working for small brokerage houses. We measure the level of analyst sophistication by the size of the brokerage house with which analysts are affiliated (*bsize_average*). The higher value of *bsize_average*, the higher level of analyst sophistication. Panel C of Table 10 shows the results for the moderating effect of analyst sophistication. The coefficient of *avg_rri_std* is negative and statistically significant for the low-analyst-sophistication subsample but is not statistically significant for the high-analyst-sophistication subsample.

4.2 Multivariate Test of the Hypothesis H2

To test the hypothesis H2 regarding the association between analyst forecast error and media coverage of ESG incidents, we specify the following OLS regression model:

$$
\begin{aligned}
error_{t+1,i} = {} & \alpha_0 + \alpha_1 avg\_rri\_std_{t,i} + \alpha_2 size_{t,i} + \alpha_3 price_{t,i} + \alpha_4 qtrret_{t,i} + \alpha_5 idiosynretvol_{t,i} \\
& + \alpha_6 intangible_{t,i} + \alpha_7 tradingvol_{t,i} + \alpha_8 insti_{t,i} + \alpha_9 btm_{t,i} + \alpha_{10} roa_{t,i} \\
& + \alpha_{11} finconstraint_{t,i} + \alpha_{12} horizon_{t,i} + \alpha_{13} change\_roa_{t,i} + \alpha_{14} change\_eps_{t,i} \\
& + \alpha_{15} surprise_{t,i} + \alpha_{16} gexp\_average_{t,i} + \alpha_{17} bsize\_average_{t,i} + \alpha_{18} yeardum \\
& + \alpha_{19} industrydum + \varepsilon_{t+1,i} \qquad (6)
\end{aligned}
$$

where *error* equals the absolute value of the difference between the actual EPS and an analyst's last forecast of annual EPS for a firm for fiscal year t+1, divided by the firm's stock price at the end of the fiscal year. If there are multiple analysts forecasting annual EPS for a firm at fiscal year t+1, the average is taken from the analysts' last forecasts of annual EPS (e.g., He et al., 2020). In line with prior studies (e.g., Lang & Lundholm, 1996; Clement, 1999; Ali et al., 2007; Tan et al., 2011; Dhaliwal et al., 2012; He et al., 2019a; Schiemann & Tietmeyer, 2022; Liu et al., 2024), a range of control variables are included: firm size (*size*), stock price (*price*), abnormal stock returns (*qtrret*), idiosyncratic return volatility (*idiosynretvol*), intangible assets (*intangible*), trading volume (*tradingvol*), institutional stock ownership (*insti*), the book-to-market ratio (*btm*), return on assets (*roa*), financial constraints (*finconstraint*), analyst forecast horizon (*horizon*), change in pre-tax return on assets (*change_roa*), change in earnings per share (*change_eps*), earnings surprise (*surprise*), analysts' forecasting experience (*gexp_average*), and the size of analysts' brokerage house (*bsize_average*). All the control variables, along with *avg_rri_std*, are measured at year t, and are defined in Appendix 3. Industry dummies and year dummies are also controlled in the regression. Column (1) under Panel A of Table 11 shows the regression results. The coefficient on *avg_rri_std* is positive and statistically significant at the 1% level, indicating that media coverage of ESG incidents increases analyst forecast error. A one-standard-deviation increase in *avg_rri_std* gives rise to a significant increase in *error* by 7.78% of its one standard deviation.

In addition, we test whether media-covered ESG incidents would lead to greater optimistic or pessimistic bias in analyst forecasts. To this end, we replace the dependent variable in Model (6) with *optimism* and *pessimism*, respectively, for the regression estimation. The construction of *optimism* and *pessimism* follows previous research (e.g., Das et al., 1998; Eames & Glover, 2003; Choi et al., 2014): *optimism* is calculated as an analyst's last EPS forecast issued for a firm for fiscal year t+1, minus the firm's actual EPS for the fiscal year, and divided by the firm's stock price at the end of the fiscal year; *optimism* equals 0 if the analyst's last forecast of EPS is lower than the firm's EPS. *pessimism* is computed as a firm's actual EPS minus an analyst's last EPS forecast issued for a firm for fiscal year t+1, divided by the firm's stock price at the end of the fiscal year. *pessimism* equals 0 if the analyst's last EPS forecast is higher than the firm's actual EPS. The average is taken of *optimism* and *pessimism* if multiple analysts make the forecasts of EPS for a firm for fiscal year t+1.

We display the regression results of forecast optimism (forecast pessimism) in Column (2) (Column (3)) under Panel A of Table 11. The coefficients on *avg_rri_std* are positive and statistically significant for both the *optimism* regression and *pessimism* regression. A one-standard-deviation increase in *avg_rri_std* causes a significant increase in *optimism (pessimism)* by 5% (7%) of its one standard deviation. These findings imply that analysts might either underestimate or overestimate the adverse impact of media-covered ESG incidents on firm performance, thus leading to either more optimistic or more pessimistic bias in their earnings forecasts.

We also conduct an ITCV test as well as an Oster test to mitigate the concern of correlated-omitted-variable(s) bias or measurement errors potentially arising in the regression estimation. The

ITCV results are reported in Panel A of Online Appendix Table A1. The absolute value of ITCV is 0.0387, which is higher than any absolute value of the impact factor (*Impact*) of variables controlled in Model (6). Panel B shows the results for the Oster test. Zero is not included in any of the Oster identified sets. Taken together, we may infer that our baseline results in Panel A of Table 11 are not driven by potential correlated-omitted-variable(s) and measurement errors. Although reverse causality is even less concerned in the analysis of the relationship between media-covered ESG issues and analyst forecast properties, we still run a 2SLS regression, using the same instruments as we do for the previous 2SLS regression, to address the plausible endogeneity concern. Panel C of Online Appendix Table A1 reports the 2SLS regression results. The second-stage regression results are qualitatively the same as those baseline results in Panel A of Table 11, suggesting that the finding of the positive association between analyst forecast error and media-covered ESG incidents is robust to controlling for potential reverse causality. The Heckman two-stage regression results, reported in Panel D of Online Appendix Table A1, provide supportive evidence that the result of the positive association between media-covered ESG incidents and analyst forecast error is immune from sample selection bias.

We further explore the role that business risk and information risk play in mediating the effect of media-covered CSI on analyst forecast error. Model (2) (Model (4)) and Model (6) are used to test the mediating effect of business risk (information risk) which is captured by *pred_stdearnings1* (*pred_bidaskspread1*). As shown in Panel B of Table 11, the coefficients on *avg_rri_std* and *pred_stdearnings1* (*pred_bidaskspread1*) are both statistically significant at the conventional level with predicted signs, suggesting that media coverage of ESG incidents heightens the business risk and information risk of firms and thereby increases analyst forecast error.

4.3 Multivariate Test of the Hypothesis H3

To test whether and how analyst forecast dispersion is correlated with media coverage of ESG incidents, we use the following OLS regression model:

$$\begin{aligned} dispersion_{t+1,i} = \alpha_0 + \alpha_1 avg\_rri\_std_{t,i} + \alpha_2 size_{t,i} + \alpha_3 price_{t,i} + \alpha_4 qtrret_{t,i} + \alpha_5 idiosynretvol_{t,i} \\ +\alpha_6 intangible_{t,i} + \alpha_7 tradingvol_{t,i} + \alpha_8 insti_{t,i} + \alpha_9 finconstraint_{t,i} + \alpha_{10} horizon_{t,i} \\ +\alpha_{11} change\_roa_{t,i} + \alpha_{12} change\_eps_{t,i} + \alpha_{13} suprise\_prioreps_{t,i} + \alpha_{14} gexp\_average_{t,i} \\ +\alpha_{15} bsize\_average_{t,i} + \alpha_{16} yeardum + \alpha_{17} industrydum + \varepsilon_{t+1,i} \qquad (7) \end{aligned}$$

where *dispersion* is measured by the standard deviation of analysts' last forecasts of EPS for a firm for fiscal year t+1, divided by the firm's stock price at the end of the fiscal year. We require that there be at least three analysts that forecast EPS for a firm for the fiscal year. Following previous studies (e.g., Brennan & Hughes, 1991; Lang & Lundholm, 1996; Hunton & McEwen, 1997; Jacob et al., 1999; Das et al., 2006; Sidhu & Tan, 2011; Lee & So, 2017), we control for a broad set of variables in Model (7): firm size (*size*), stock price (*price*), abnormal stock returns (*qtrret*), idiosyncratic return volatility (*idiosynretvol*), intangible assets (*intangible*), stock trading volume (*tradingvol*), institutional stock ownership (*insti*), financial constraints (*finconstraint*), analyst forecast horizon (*horizon*), change in pre-tax return on assets (*change_roa*), change in earnings per share (*change_eps*), earnings surprise (*surprise_prioreps*), analysts' forecasting experience (*gexp_average*), and the size of analysts' brokerage house (*bsize_average*). We measure all these variables, along with *avg_rri_std*, at year t, and provide their definitions in Appendix 3. We also control for industry dummies and year dummies in the regression.

Panel A of Table 12 shows the OLS regression results from running Model (7). The coefficient of *avg_rri_std* is positive and statistically significant at the 1% level, providing support for our conjecture that analyst forecast dispersion is positively correlated with media coverage of ESG incidents. A one-standard-deviation increase in *avg_rri_std* gives rise to a significant increase in *dispersion* by 8.44% of its one standard deviation. We also conduct the ITCV test, Oster estimates, 2SLS regression analysis, and Heckman two-stage regression, similar to what we do previously, to allay the potential concern as to correlated-omitted-variable(s) bias, measurement errors, reverse causality, and sample selection bias. As seen in Online Appendix Table A2, our regression results for Model (7) are robust under all these tests. Lastly, the results reported in Panel B of Table 12 suggest that the increased business risk and heightened information risk are the underlying mechanisms that explain the aggravating effect of media-covered ESG incidents on analyst forecast dispersion.

5. Conclusion

Though corporate social irresponsibility (CSI) could trigger substantial economic and social consequences on firms, the market consequences and value impacts of CSI depend on how well CSI is known to widespread stakeholders. The media plays a crucial role in broadcasting CSI behavior to a wide range of stakeholders. In this paper, we examine how financial analysts, the crucial information intermediaries in the financial marketplace, respond to media-covered ESG incidents.

Based on a sample of U.S. listed companies, we find that media-covered ESG incidents are associated with reduced analyst coverage. The result persists after controlling for potential endogeneity problems and is more pronounced for firms with more intense industrial product market competition, more severe ESG incidents, and higher coverage by less-sophisticated analysts. Our mechanism tests further reveal that business risk and information risk are higher for firms that are subject to media-covered ESG incidents, thereby explaining why analyst coverage is lower for these firms. Furthermore, we find both statistically and economically significant evidence to suggest that analyst forecasts are adversely affected by media-covered ESG incidents. In particular, the media coverage increases the business risk and information risk of firms and thereby enlarges the error and dispersion of analyst forecasts to a larger extent. Analysts seem to lack sophistication in processing information that has considerably uncertain implications for the firm's future prospect. The reduced analyst coverage, along with the significantly increased forecast error and forecast dispersion, imply the undermining of analysts' information-intermediary role and plausible consequential reduction in capital market efficiency. These potential consequences thus underline the importance for regulators and firms to curb CSI. To this end, it is essential to enhance the transparency and accountability in corporate governance in terms of ESG practices. Regulators or firms may introduce and enforce policies that mandate more comprehensive and frequent corporate reporting and stronger risk controls on ESG issues. These include implementing stricter disclosure requirements for firms' ESG issues, making regular ESG risk assessments, and incorporating ESG metrics into the performance evaluation and compensation schemes for managers and directors. Such initiatives would not only facilitate firms to improve their ESG practices but also ensure that the firms' stakeholders have consistent access to quality ESG information to restrain potential ESG misconduct.

Our findings also imply a need for analysts to enhance their understanding of how media coverage of ESG incidents influences their works. Specifically, the increased business risk and information risk as a result of the media's coverage necessitate adjustments in their evaluation metrics and forecasting approaches to mitigate the risk of increased forecast error. They should endeavor to improve their performance in the forecasting for socially irresponsible firms, particularly those that are subject to media coverage of ESG incidents.

To the extent that the establishment of a causal effect on analyst coverage and forecasts is difficult, some studies (e.g., Bradshaw et al., 2006; Jiang et al., 2016; Bilinski & Bradshaw, 2022; Huang et al., 2022) focus on documenting the association rather than causality for the determinants of analyst behavior and do not account for potential endogeneity concerns in their analyses. While our study goes a considerable way in mitigating the endogeneity problem, we concede that it is not resolved completely. That said, our paper should advance the understanding of the economic consequence of CSI by way of shedding light on its impact on analyst coverage and forecasts.

References

Aboody, D., & Lev, B. (2000). Information asymmetry, R&D, and insider gains. *Journal of Finance*, 55(6), 2747-2766. https://doi.org/10.1111/0022-1082.00305

Ali, A., Chen, T. Y., & Radhakrishnan, S. (2007). Corporate disclosures by family firms. *Journal of Accounting and Economics*, 44(1-2), 238-286. https://doi.org/10.1016/j.jacceco.2007.01.006

Armstrong, C., Kepler, J. D., Samuels, D., & Taylor, D. (2022). Casualty redux: The evolution of empirical methods in accounting research and the growth of quasi-experiments. *Journal of Accounting and Economics*, 74(2-3), 101521. https://doi.org/10.1016/j.jacceco.2022.101521

Ashbaugh-Skaife, H., Collins, D. W., & Kinney, Jr W. R. (2007). The discovery and reporting of internal control deficiencies prior to SOX-mandated audits. *Journal of Accounting and Economics*, 44(1-2), 166-192. https://doi.org/10.1016/j.jacceco.2006.10.001

Barnett, M. L. (2014). Why stakeholders ignore firm misconduct: A cognitive view. *Journal of Management*, 40(3), 676-702. https://doi.org/10.1177/0149206311433854

Barth, M. E., Kasznik, R., & McNichols, M. F. (2001). Analyst coverage and intangible assets. *Journal of Accounting Research*, 39(1), 1-34. https://doi.org/10.1111/1475-679X.00001

Bednar, M. K., Boivie, S., & Prince, N. R. (2013). Burr under the saddle: How media coverage influences strategic change. *Organization Science*, 24(3), 910-925. https://doi.org/10.1287/orsc.1120.0770

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research*, 27, 1-36. https://doi.org/10.2307/2491062

Bhattacharya, N., Ecker, F., Olsson, P. M., & Schipper, K. (2012). Direct and mediated associations among earnings quality, information asymmetry, and the cost of equity. *The Accounting Review*, 87(2), 449-482. https://doi.org/10.2308/accr-10200

Bhushan, R. (1989). Firm characteristics and analyst following. *Journal of Accounting and Economics*, 11(2-3), 255-274. https://doi.org/10.1016/0165-4101(89)90008-6

Bilinski, P., & Bradshaw, M. T. (2022). Analyst dividend forecasts and their usefulness to investors. *The Accounting Review*, 97(4), 75-104. https://doi.org/10.2308/TAR-2018-0518

Bradshaw, M. T., Lock, B., Wang, X., & Zhou, D. (2021). Soft information in the financial press and analyst revisions. *The Accounting Review*, 96(5), 107-132. https://doi.org/10.2308/TAR-2018-0264

Bradshaw, M. T., Richardson, S. A., & Sloan, R. G. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics*, 42(1-2), 53-85. https://doi.org/10.1016/j.jacceco.2006.03.004

Braunsberger, K., & Buckler, B. (2011). What motivates consumers to participate in boycotts: Lessons from the ongoing Canadian seafood boycott. *Journal of Business Research*, 64(1), 96-102. https://doi.org/10.1016/j.jbusres.2009.12.008

Brennan, M. J., & Hughes, P. J. (1991). Stock prices and the supply of information. *The Journal of Finance*, 46 (5), 1665-1691. https://doi.org/10.1111/j.1540-6261.1991.tb04639.x

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, 73, 305-333.

Campello, M., Graham, J. R., & Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, 97(3), 470-487. https://doi.org/10.1016/j.jfineco.2010.02.009

Cao, Y., Myers, J. N., Myers, L. A., & Omer, T. C. (2015). Company reputation and the cost of equity capital. *Review of Accounting Studies*, 20, 42-81. https://doi.org/10.1007/s11142-014-9292-9

Chandra, U., Procassini, A., & Waymire, G. (1999). The use of trade association disclosures by investors and analysts: Evidence from the semiconductor industry. *Contemporary Accounting Research*, 16(4), 643-670. https://doi.org/10.1111/j.1911-3846.1999.tb00599.x

Chang, X., Dasgupta, S., & Hilary, G. (2006). Analyst coverage and financing decisions. *Journal of Finance*, 61(6), 3009-3048. https://doi.org/10.1111/j.1540-6261.2006.01010.x

Chen, Z., Hang, H., Pavelin, S., & Porter, L. (2020). Corporate social (ir)responsibility and corporate hypocrisy: Warmth, motive, and the protective value of corporate social responsibility. *Business Ethics Quarterly*, 30(4), 486-524. https://doi.org/10.1017/beq.2019.50

Chen, L., He, G., & Krishnan, G. V. (2023). Does CEO debt-like compensation mitigate corporate social irresponsibility? *Accounting Forum*, 1-44. https://doi.org/10.1080/01559982.2023.2195983

Choi, K. W., Chen, X., Wright, S., & Wu, H. (2014). Analysts' forecasts following forced CEO changes. *Abacus*, 50(2), 146-173. https://doi.org/10.1111/abac.12026

Chung, R., Firth, M., & Kim, J. B. (2002). Institutional monitoring and opportunistic earnings management. *Journal of Corporate Finance*, 8(1), 29-48. https://doi.org/10.1016/S0929-1199(01)00039-6

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 27(3), 285-303. https://doi.org/10.1016/S0165-4101(99)00013-0

Cowling, M. (2004). The growth-profit nexus. *Small Business Economics*, 22(1), 1-9. https://doi.org/10.1023/B:SBEJ.0000011568.42714.c9

Cox, P., Brammer, S., & Millington, A. (2004). An empirical examination of institutional investor preferences for corporate social performance. *Journal of Business Ethics*, 52, 27-43. https://doi.org/10.1023/B:BUSI.0000033105.77051.9d

Das, S., Guo, R. J., & Zhang, H. (2006). Analysts' selective coverage and subsequent performance of newly public firms. *The Journal of Finance*, 61(3), 1159-1185. https://doi.org/10.1111/j.1540-6261.2006.00869.x

Das, S., & Levine, C. B., Sivaramakrishnan, K. (1998). Earnings predictability and bias in analysts' earnings forecasts. *The Accounting Review*, 73(2), 277-294.

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. *The Accounting Review*, 70, 193-225.

Demiralp, I., D'Mello, R., Schlingemann, F. P., & Subramaniam, V. (2011). Are there monitoring benefits to institutional ownership? Evidence from seasoned equity offerings. *Journal of Corporate Finance*, 17(5), 1340-1359. https://doi.org/10.1016/j.jcorpfin.2011.07.002

Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., & Yang, Y. G. (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review*, 87(3), 723-759. https://doi.org/10.2308/accr-10218

Eames, M. J., & Glover, S. M. (2003). Earnings predictability and the direction of analysts' earnings forecast errors. *The Accounting Review*, 78(3), 707-724. https://doi.org/10.2308/accr.2003.78.3.707

Fang, L. H., & Yasuda, A. (2014). Are stars' opinions worth more? The relation between analyst reputation and recommendation values. *Journal of Finance Services Research*, 46, 235-269. https://doi.org/10.1007/s10693-013-0178-y

Feldman, R., Govindaraj, S., Livnat, J., & Segal, B. (2010). Management's tone change, post earnings announcement drift and accruals. *The Review of Accounting Studies*, 15, 915-953. https://doi.org/10.1007/s11142-009-9111-x

Flammer, C. (2013). Corporate social responsibility and shareholder reaction: The environmental awareness of investors. *Academy of Management Journal*, 56(3), 758-781. https://doi.org/10.5465/amj.2011.0744

Fombrun, C. J. (1996). *Reputation: Realizing value from the corporate image*. Boston: Harvard Business School Press.

Fombrun, C., & Shanley, M. (1990). What's in a name? Reputation building and corporate strategy. *Academy of Management Journal*, 33(2), 233-258. https://doi.org/10.5465/256324

Fontes, J. C., Panaretou, A., & Peasnell, K. V. (2018). The impact of fair value measurement for bank assets on information asymmetry and the moderating effect of own credit risk gains and losses. *The Accounting Review*, 93(6), 127-147. https://doi.org/10.2308/accr-52070

Francis, J., Lafond, R., Olsson, P., & Schipper, K. (2007). Information uncertainty and post-earnings-announcement-drift. *Journal of Business, Finance, and Accounting*, 34(3-4), 403-433. https://doi.org/10.1111/j.1468-5957.2007.02030.x

Frank, K. A. (2000). Impact of a confounding variable on a regression coefficient. *Sociological Methods & Research*, 29 (2), 147-194. https://doi.org/10.1177/0049124100029002001

Frankel, R., Kothari, S. P., & Weber, J. (2006). Determinants of the informativeness of analyst research. *Journal of Accounting Economics*, 41(1-2), 29-54. https://doi.org/10.1016/j.jacceco.2005.10.004

Ge, W., & McVay, S. (2005). The disclosure of material weaknesses in internal control after the Sarbanes-Oxley Act. *Accounting Horizons*, 19(3), 137-158. https://doi.org/10.2308/acch.2005.19.3.137

Grappi, S., Romani, S., & Bagozzi, R. P. (2013), Consumer response to corporate irresponsible behavior: Moral emotions and virtues. *Journal of Business Research*, 66(10), 1814-1821. https://doi.org/10.1016/j.jbusres.2013.02.002

Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5), 1909-1940. https://doi.org/10.1093/rfs/hhq009

Hansen, S. D., Dunford, B. B., Boss, A. D., Boss, R. W., & Angermeier, I. (2011). Corporate social responsibility and the benefits of employee trust: A cross-disciplinary perspective. *Journal of Business Ethics*,102: 29-45. https://doi.org/10.1007/s10551-011-0903-0

He, F., Guo, X., & Yue, P. (2024). Media coverage and corporate ESG performance: Evidence from China. *International Review of Financial Analysis*, 91, 103003. https://doi.org/10.1016/j.irfa.2023.103003

He, G. (2021) Credit rating, post-earnings-announcement drift, and arbitrage from transient institutions. *Journal of Business, Finance, and Accounting*, 48(7-8), 1434 -1467. https://doi.org/10.1111/jbfa.12520

He, G., Bai, L., & Ren, H. M. (2019b). Analyst coverage and future stock price crash risk. *Journal of Applied Accounting Research*, 20(1), 63-77. https://doi.org/10.1108/JAAR-09-2017-0096

He, G., Marginson, D., & Dai, X. (2019a). Do voluntary disclosures of product and business expansion plans impact analyst coverage and forecasts? *Accounting and Business Research*, 49(7), 785-817. https://doi.org/10.1080/00014788.2018.1559717

He, G., Ren, H. M., & Taffler, R. (2020) The impact of corporate tax avoidance on analyst coverage and forecasts. *Review of Quantitative Finance and Accounting*, 54(2), 447-477. https://doi.org/10.1007/s11156-019-00795-7

He, G., Li, Z., & Slack, R. (2023). The economic consequences of corporate social irresponsibility and policy implications. In: *Climate Change and Climate Finance: Current Experience and Future Directions, edited by Fariborz Moshirian & Cyn-Young Park*. Chapter 5, pages 60-86, Publisher: Asian Development Bank.

Herzig, C., & Moon, J. (2013). Discourses on corporate social ir/responsibility in the financial sector. *Journal of Business Research*, 66(10), 1870-1880. https://doi.org/10.1016/j.jbusres.2013.02.008

Huang, A. H., Lin, A. P., & Zhang, A. Y. (2022). Cross-industry information sharing among colleagues and analyst research. *Journal of Accounting and Economics*, 74(1), 101496. https://doi.org/10.1016/j.jacceco.2022.101496

Huddart, S. J., & Ke, B. (2007). Information asymmetry ad cross-sectional variation in insider trading. *Contemporary Accounting Research*, 24(1), 195-232. https://doi.org/10.1506/0277-1110-4434-M627

Hunton, J. E., & McEwen, R. A. (1997). An assessment of the relation between analysts' earnings forecast accuracy, motivational incentives, and cognitive information search strategy. *The Accounting Review*, 72(4), 497-515.

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, 94(1), 67-86. https://doi.org/10.1016/j.jfineco.2008.10.003

Jacob, J., Lys, T. Z., & Neale, M. A. (1999). Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics*, 28(1), 51-82. https://doi.org/10.1016/S0165-4101(99)00016-6

Jiang, D., Kumar, A., & Law, K. K. F. (2016). Political contributions and analyst behavior. *Review of Accounting Studies*, 21, 37-88. https://doi.org/10.1007/s11142-015-9344-9

Johnson, R. A., & Greening, D. W. (1999). The effects of corporate governance and institutional ownership types on corporate social performance. *Academy of Management Journal*, 42(5), 564-576. https://doi.org/10.5465/256977

Kang, C., Germann, F., & Grewal, R. (2016). Washing away your sins? Corporate social responsibility, corporate social irresponsibility, and firm performance. *Journal of Marketing*, 80(2), 59-79. https://doi.org/10.1509/jm.15.0324

Karpoff, J. M., Lee, D. S., & Martin, G. S. (2008). The cost to firms of cooking the books. *Journal of Financial and Quantitative Analysis*, 43(3), 581-611. https://doi.org/10.1017/S0022109000004221

Karuna, C. (2007). Industry product market competition and managerial incentives. *Journal of Accounting and Economics*, 43(2-3), 275-297. https://doi.org/10.1016/j.jacceco.2007.02.004

Keig, D. L., Brouthers, L. E., & Marshall, V. B. (2015). Formal and informal corruption environments CSIR: Review and multinational enterprise social irresponsibility. *Journal of Management Studies*, 52(1), 89-116. https://doi.org/10.1111/joms.12102

Khan, M., Serafeim, G., & Yoon, A. (2016). Corporate sustainability: First evidence on materiality. *The Accounting Review*, 91(6), 1697-1724. https://doi.org/10.2308/accr-51383

Klein, J., & Dawar, N. (2004). Corporate social responsibility and consumers' attributions and

brand evaluations in a product-harm crisis. *International Journal of Research in Marketing*, 21(3), 203-217. https://doi.org/10.1016/j.ijresmar.2003.12.003
Klein, B., & Leffler, K. B. (1981). The role of market forces in assuring contractual performance. *Journal of Political Economy*, 89(4), 615-641. https://doi.org/10.1086/260996
Kölbel, J. F., Busch, T., & Jancso, L. M. (2017). How media coverage of corporate social irresponsibility increases financial risk. *Strategic Management Journal*, 38(11), 2266-2284. https://doi.org/10.1002/smj.2647
Konstantinidi, T., & Pope, P. F. (2016). Forecasting risk in earnings. *Contemporary Accounting Research*, 33(2), 487-525. https://doi.org/10.1111/1911-3846.12158
Kothari, S. P., So, E., & Verdi, R. (2016). Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics*, 8, 197-219. https://doi.org/10.1146/annurev-financial-121415-032930
Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research*, 47(1), 241-276. https://doi.org/10.1111/j.1475-679X.2008.00318.x
Kraay, A. (2002). *Exports and economic performance: Evidence from a panel of Chinese enterprises*. In M. Renard, (ed.), China and its Regions, Edward Elgar Publishing, Cheltenham, UK.
Krishnan, G. V. (2003). Does Big 6 auditor industry expertise constrain earnings management? *Accounting Horizons*, 17, 1-16.
Lambert, R. A., Leuz, C., & Verrecchia, R. E. (2012). Information asymmetry, information precision, and the cost of capital. *Review of Finance*, 16(1), 1-29. https://doi.org/10.1093/rof/rfr014
Lang, M. H., & Lundholm, R. J. (1996). Corporate disclosure policy and analyst behavior. *The Accounting Review*, 71(4), 467-492.
Larcker, D. F., & Rusticus, T. O. (2010). On the use of instrumental variables in accounting research. *Journal of Accounting and Economics*, 49(3), 186-205. https://doi.org/10.1016/j.jacceco.2009.11.004
Lee, J. (2009). Does size matter in firm performance? Evidence from US public firms. *International Journal of the Economics of Business*, 16(2), 189-203. https://doi.org/10.1080/13571510902917400
Lee, C. M. C., & So, E. C. (2017). Uncovering expected returns: Information in analyst coverage proxies. *Journal of Financial Economics*, 124(2), 331-348. https://doi.org/10.1016/j.jfineco.2017.01.007
Lehavy, R. , Li, F., & Merkley, K. (2011). The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, 86(3), 1087-1115. https://doi.org/10.2308/accr.00000043
Lenz, I., Wetzel, H. A., & Hammerschmidt, M. (2017). Can doing good lead to doing poorly? Firm value implications of CSR in the face of CSI. *Journal of the Academy of Marketing Science*, 45, 677-697. https://doi.org/10.1007/s11747-016-0510-9
Lev, B. (2001). *Intangibles – Management, measurement, and reporting*. Washington: Brookings Institution Press, 1-213.
Li, W., Padmanabhan, P., & Huang, C. (2024). ESG and debt structure: Is the nature of this relationship nonlinear? *International Review of Financial Analysis*, 91, 103027. https://doi.org/10.1016/j.irfa.2023.103027
Lin, H., Zeng, S., Wang, L., Zou, H., & Ma, H. (2016). How does environmental irresponsibility impair corporate reputation? A muti-method investigation. *Corporate Social Responsibility*

and Environmental Management, 23(6), 413-423. https://doi.org/10.1002/csr.1387
Lindenmeier, J., Schleer, C., & Pricl, D. (2012) Consumer outrage: Emotional reactions to unethical corporate behavior. *Journal of Business Research*, 65(9), 1364-1373. https://doi.org/10.1016/j.jbusres.2011.09.022
Liu, C., Zhou, Z., Su, K., Liu, K., & An, H. (2024). Water risk and financial analysts' information environment: Empirical evidence from China. *Businss Strategy and the Enviroment*, 33(2):1265-1304. http://doi.org/10.1002/bse.3539
Mendenhall, R. R. (2004). Arbitrage risk and post-earnings-announcement drift. *The Journal of Business*, 77(4), 875-894. https://doi.org/10.1086/422627
Mohr, L. A., & Webb, D. J. (2005). The effect of corporate social responsibility and price on consumer responses. *Journal of Consumer Affairs*, 39(1), 121-147. https://doi.org/10.1111/j.1745-6606.2005.00006.x
Muller, K. A., Riedl, E. J., & Sellhorn, T. (2011). Mandatory fair value accounting and information asymmetry: Evidence from the European real estate industry. *Management Science*, 57(6), 1138-1153. https://doi.org/10.1287/mnsc.1110.1339
O'Brien, P. C., & Bhushan, R. (1990). Analyst following and institutional ownership. *Journal of Accounting Research*, 28, 55-76. https://doi.org/10.2307/2491247
Oikonomou, I., Brooks, C., & Pavelin, S. (2014). The effects of corporate social performance on the cost of corporate debt and credit ratings. *The Financial Review*, 49(1), 49-75. https://doi.org/10.1111/fire.12025
Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business and Economic Statistics*, 37(2), 187-204. https://doi.org/10.1080/07350015.2016.1227711
Philippe, D., & Durand, R. (2011). The impact of norm-conforming behaviors on firm reputation. *Strategic Management Journal*, 32(9), 969-993. https://doi.org/10.1002/smj.919
Pinnuck, M., Ranasinghe, A., Soderstrom, N., & Zhou, J. (2021). Restatement of CSR reports: Frequency, magnitude, and determinants. *Contemporary Accounting Research*, 38(3), 2376-2416. https://doi.org/10.1111/1911-3846.12666
Rahman, J. M., Zhang, J., & Dong, S. (2019). Factors affecting the accuracy of analysts' forecasts: A review of the literature. *Academy of Accounting and Financial Studies Journal*, 23(3), 1-18. https://ssrn.com/abstract=3610334 Accessed 9 September 2023.
Rajgopal, S., Shevlin, T., & Venkatachalam, M. (2003). Does the stock market fully appreciate the implications of leading indicators for future earnings? *Evidence from order backlog. Review of Accounting Studies*, 8, 461-492. https://doi.org/10.1023/A:1027364031775
RepRisk. (2018). Available at http://www.reprisk.com as of 2018.
Rojo-Suarez, J., & Alonso-Conde, A. B. (2024). Have shifts in investor tastes led the market portfolio to capture ESG preferences. *International Review of Financial Analysis*, 91, 103019. https://doi.org/10.1016/j.irfa.2023.103019
Rountree, B., Weston, J. P., & Allayannis, G. (2008). Do investors value smooth performance? *Journal of Financial Economics*, 90(3), 237-251. https://doi.org/10.1016/j.jfineco.2008.02.002
Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review*, 5(4), 296-320. https://doi.org/10.1207/S15327957PSPR0504_2
Ryan, L. V., & Schneider, M. (2002). The antecedents of institutional investor activism. *Academy of Management Review*, 27(4), 554-573. https://doi.org/10.5465/amr.2002.7566068

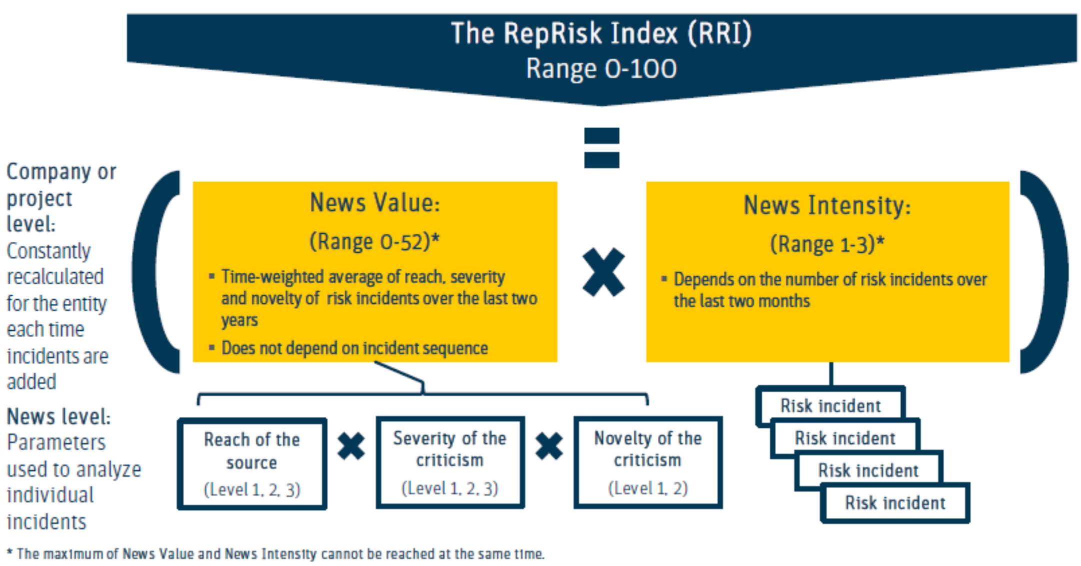
Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, 80(2), 309-349. https://doi.org/10.1016/j.jfineco.2005.04.005
Schiemann, F., & Tietmeyer, R. (2022). ESG controversies, ESG disclosure and analyst forecast accuracy. *International Review of Financial Analysis*, 84, 102373. https://doi.org/10.1016/j.irfa.2022.102373
Shapiro, C. (1983). Premiums for high-quality products as returns to reputations. *The Quarterly Journal of Economics*, 98(4), 659-679. https://doi.org/10.2307/1881782
Shleifer, A., & Vishny, R. W. (1986). Large shareholders and corporate control. *Journal of Political Economy*, 94(3, Part 1), 461-488. https://doi.org/10.1086/261385
Siconolfi, M. (1995). Incredible 'buys': Many companies press analysts to steer clear of negative ratings. *The Wall Street Journal*, A. I.
Sidhu, B., Tan, H. C. (2004). The performance of equity analysts during the global financial crisis. *Australian Accounting Review*, 21(1), 32-43. https://doi.org/10.1111/j.1835-2561.2010.00116.x
Simpson, A. (2010). Analysts' use of nonfinancial information disclosures. *Contemporary Accounting Research*, 27(1), 249-288. https://doi.org/10.1111/j.1911-3846.2010.01008.x
Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in the generalized method of moments. *Journal of Business and Economic Statistics*, 20(4), 518-529. https://doi.org/10.1198/073500102288618658
Strike, V. M., Gao, J., & Bansal, P. (2006). Being good while being bad: Social responsibility and the international diversification of US firms. *Journal of International Business Studies*, 37, 850-862. https://doi.org/10.1057/palgrave.jibs.8400226
Sweetin, V. H., Knowles, L. L., Summey, J. H., & McQueen, K. S. (2013). Willingness-to-punish the corporate brand for corporate social irresponsibility. *Journal of Business Research*, 66(10), 1822-1830. https://doi.org/10.1016/j.jbusres.2013.02.003
Tan, H., Wang, S., & Welker, M. (2011). Analyst following and forecast accuracy after mandated IFRS adoptions. *Journal of Accounting Research*, 49(5), 1307-1357. https://doi.org/10.1111/j.1475-679X.2011.00422.x
Trueman, B. (1994). Analyst forecasts and herding behavior. *Review of Financial Studies*, 7(1), 97-124. https://doi.org/10.1093/rfs/7.1.97
Warfield, T. D., Wild, J. J., & Wild, K. L. (1995). Managerial ownership, accounting choices, and informativeness of earnings. *Journal of Accounting and Economics*, 20(1), 61-91. https://doi.org/10.1016/0165-4101(94)00393-J
Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, 19(2), 531-559. https://doi.org/10.1093/rfs/hhj012
Wiesenfeld, B. M., Wurthmann, K. A., & Hambrick, D. C. (2008). The stigmatization and devaluation of elites associated with corporate failures: A process model. *Academic of Management Review*, 33(1), 231-251. https://doi.org/10.5465/amr.2008.27752771
Wong, J. B., & Zhang, Q. (2022). Stock market reactions to adverse ESG disclosure via media channels. *The British Accounting Review*, 54(1), 101045. https://doi.org/10.1016/j.bar.2021.101045
Zhang, C., & Wu, X. (2023). Analyst coverage and corporate ESG performance. *Sustainability*, 15 (17), 12763. https://doi.org/10.3390/su151712763

Appendix 1: Research scope of RepRisk database

Environmental issues	Social issues	Governance issues
• Animal mistreatment • Climate changes, greenhouse gas emissions, and global pollution • Impacts on ecosystems, landscapes, and biodiversity • Local pollution • Overuse and wasting of resources • Waste issues	• Child labor • Discrimination in employment • Forced labor • Freedom of association and collective bargaining • Human rights abuses and corporate complicity • Impacts on communities • Local participation issues • Occupational health and safety issues • Poor employment conditions • Social discrimination	• Anti-competitive practices • Corruption, bribery, extortion, and money laundering • Executive compensation issues • Fraud • Misleading communication • Tax evasion • Tax optimization
Cross-cutting issues		
• Controversial products and services • Products (health and environmental issues) • Violation of international standards • Violation of national legislation • Supply chain issues		

Source: The information in this table is available from https://insight.factset.com/resources/at-a-glance-reprisk-data-feed.

Appendix 2: Proprietary algorithm of RepRisk Index (RRI)



Source: This graph was obtained from http://www.reprisk.com.

Appendix 3: Summary of variable definitions

Variables	Definitions
lnanacov	The natural logarithm of 1 plus the number of analysts that make at least one annual EPS forecast for a firm over a fiscal year. *lnanacov* equals 0 if there is no analyst forecasting annual EPS for a firm over the fiscal year.
avg_rri_std	The average monthly RRI score in a fiscal year, scaled by the standard deviation of monthly RRI scores.
avg_rri	The average monthly RRI score in a fiscal year.
size	The natural logarithm of the market value of a firm's equity at the end of a fiscal year.
idiosynretvol	The standard deviation of the residuals from the following regression model over the past 52 weeks as of the earnings announcement date for the fiscal quarter: $r_{i,t}=\alpha_i+\beta_{1i}r_{m,t}+ \beta_{2i}r_{m,t+1}+ \beta_{3i}r_{m,t+2}+ \beta_{4i}r_{m,t-1}+ \beta_{5i}r_{m,t-2}+\varepsilon_{i,t}$ where $r_{i,\,t}$ is the weekly return on stock i, and $r_{m,\,t}$ is the value-weighted Center for Research in Security Prices (CRSP) index return.
price	The stock price of a firm at the fiscal year-end date.
qtrret	The buy-and-hold size-adjusted abnormal stock returns of a firm for a fiscal year.
roa	Net income before extraordinary items for a fiscal year, divided by total assets, at the end of the fiscal year.
finconstraint	a financial constraint index developed by Hadlock and Pierce (2010). SA=-0.737*size+0.043*size2-0.040*age, where size is the natural logarithm of total assets capped at $4.5 billion, and age is the number of years for which a firm has been listed. The SA index is re-scaled by dividing 1,000 to get the value for *finconstraint*.
r&d	1 if the research and development expense of a firm is positive for a fiscal year, and 0 otherwise.
intangible	1 if a firm has intangible assets for a fiscal year, and 0 otherwise.
btm	The book value of firm equity divided by the market value of firm equity at the end of a fiscal year.
insti	Institutional investors' stock ownership as a percentage of the total outstanding shares for a firm at the end of a fiscal year.
tradingvol	Daily dollar trading volume (i.e., the closing price at a given date times the number of shares traded at that date) (in millions of U.S. dollars) averaged over a fiscal year for a firm.
regulated	1 if a firm belongs to a regulated industry (with standard industrial classification (SIC) coded 4900-4999, 6000-6411, and 6500-6999), and 0 otherwise.
esg_risks_industry	The average value of *avg_rri_std* for each of the SIC industries in a fiscal year.
lyr_esg	The natural logarithm of one plus the total news count on environmental, social, and governance issues during a fiscal year.
lyr_esg_industry	The natural logarithm of one plus the total news count on a firm's environmental, social, and governance issues for each of the SIC industries in a fiscal year.
competition	A composite measure of two proxies for industrial product market competition, *substitution* and *mktsize*, which is derived from using common factor analysis.
ESG_dummy	1 if a firm has media coverage of ESG incidents, and 0 otherwise.
imr	The Inverse Mills ratio that is estimated in the first step of Heckman two-stage regression.
stdearnings	The standard deviation of net incomes before extraordinary items in the current and previous four years (the net incomes before extraordinary items are measured in thousands).

salesgrowth	Sales revenues for fiscal year t minus sales revenues for fiscal year t-1, scaled by sales revenues for fiscal year t-1.
pred_stdearnings	The predicted value of *stdearnings* estimated from Equation (2) when examining the mediating effect of business risk on the association between media coverage of ESG incidents and analyst coverage.
bidaskspread	Bid-ask spreads, which are estimated by using daily relative effective spreads averaged over a fiscal year for a firm.
auditfee	The natural logarithm of the ratio of audit fees to total assets of a firm at a fiscal year.
pred_bidaskspread	The predicted value of *bidaskspread* estimated from Equation (4) when examining the mediating effect of information risk on the association between media coverage of ESG incidents and analyst coverage.
substitution	A proxy for industrial product market competition, which equals the sum of the sales of all firms in a 2-digit SIC industry for a fiscal year, divided by the sum of operating costs of each firm in the same industry.
mktsize	A proxy for industrial product market competition, which equals the sum of sales of all firms in a 2-digit SIC industry for a fiscal year (in millions of U.S. dollars).
severity	0 if the ESG incidents of a firm is defined by RepRisk as of low severity in a fiscal year, and 1 otherwise.
error	The absolute value of the difference between the actual EPS and an analyst's last forecast of annual EPS for a firm for a fiscal year, divided by the firm's stock price at the end of the fiscal year. If there are multiple analysts forecasting annual EPS for a firm for the fiscal year, the average is taken of the analysts' last forecasts of annual EPS.
horizon	The natural logarithm of the number of days between an analyst's last annual EPS forecast date and a firm's earnings announcement date. If there are multiple analysts that forecast annual EPS for a firm for a fiscal year, the average is taken of the number of days between analysts' last EPS forecast dates and a firm's earnings announcement date.
change_roa	Return on assets of a firm for a fiscal year minus that for the previous fiscal year. Return on assets is computed as net income before extraordinary items for a fiscal year, divided by total assets at the end of the fiscal year.
change_eps	Annual EPS of a firm for a fiscal year, minus that for the previous year, and divided by stock price at the end of the fiscal year.
surprise	The actual EPS minus the median of analysts' annual EPS forecasts for a firm for a fiscal year, divided by the median of the analysts' annual EPS forecasts.
gexp_average	A proxy for an analyst's general forecasting experience, which equals the natural logarithm of the number of years since an analyst's first earnings forecast appeared in the I/B/E/S database for a firm for a fiscal year. If a firm's earnings are forecasted by multiple analysts for a fiscal year, the average is taken of the analysts' general forecasting experience.
bsize_average	A proxy for the size of brokerage house with which an analyst is affiliated, which equals the natural logarithm of the number of analysts of a brokerage house in a fiscal year. If a firm's earnings are forecasted by multiple analysts for a fiscal year, the average is taken of the sizes of the brokerage houses with which the analysts are affiliated.
pred_stdearnings1	The predicted value of *stdearnings* estimated from Equation (2) when examining the mediating effect of business risk on the association between media coverage of ESG incidents and analyst forecast error.

pred_bidaskspread1	The predicted value of *bidaskspread* estimated from Equation (4) when examining the mediating effect of information risk on the association between media coverage of ESG incidents and analyst forecast error.
optimism	An analyst's last EPS forecast issued for a fiscal year, minus a firm's actual EPS for the fiscal year, divided by the firm's stock price at the end of the fiscal year. *optimism* equals 0 if a firm's actual EPS is higher than the analyst's last forecast of EPS. Average is taken of *optimism* if multiple analysts make the forecasts of EPS for a firm for the fiscal year.
pessimism	A firm's actual EPS minus an analyst's last EPS forecast issued for a fiscal year, divided by the stock price of a firm at the end of the fiscal year. *pessimism* equals 0 if a firm's actual EPS is lower than the analyst's last forecast of EPS. Average is taken of *pessimism* if multiple analysts make the forecasts of EPS for a firm for the fiscal year.
dispersion	The standard deviation of analysts' last forecasts of annual EPS for a firm for a fiscal year, divided by the firm's stock price at the end of the fiscal year. In constructing *dispersion*, it is required that there are at least three analysts who forecast annual EPS for a firm for the fiscal year.
surprise_prioreps	The actual EPS for a firm at a fiscal year minus the actual EPS at the previous year, divided by the actual EPS at the previous year.
pred_stdearnings2	The predicted value of *stdearnings* estimated from Equation (2) when examining the mediating effect of business risk on the association between media coverage of ESG incidents and analyst forecast dispersion.
pred_bidaskspread2	The predicted value of *bidaskspread* estimated from Equation (4) when examining the mediating effect of information risk on the association between media coverage of ESG incidents and analyst forecast dispersion.

Table 1: Media-covered ESG incidents (*avg_rri_std*) and analyst coverage (*lnanacov*) across years and industries

Panel A: The distribution and statistics of *avg_rri_std* and *lnanacov* across years

Year	*avg_rri_std*							
	N	Mean	10%	25%	Median	75%	90%	Std. dev.
2007	72	2.211	0.327	0.590	1.326	2.853	4.943	3.144
2008	120	2.654	0.713	1.025	2.216	3.603	5.499	2.043
2009	145	2.830	0.610	1.055	2.177	3.599	6.460	2.274
2010	169	2.469	0.402	0.759	1.575	3.300	5.499	2.426
2011	246	2.954	0.500	1.044	2.265	3.754	6.958	2.509
2012	451	3.751	0.592	1.421	3.092	5.294	7.544	3.877
2013	570	3.214	0.592	0.931	2.440	4.657	6.832	3.130
2014	638	3.633	0.592	1.139	2.669	5.069	7.805	4.074
2015	686	3.916	0.486	1.087	2.819	5.315	8.739	4.104

Year	*lnanacov*							
	N	Mean	10%	25%	Median	75%	90%	Std. dev.
2008	72	4.147	3.178	3.597	4.304	4.649	5.112	0.844
2009	120	3.970	2.674	3.401	4.086	4.585	5.170	0.912
2010	145	3.898	2.773	3.367	4.060	4.654	5.030	1.098
2011	169	3.853	2.398	3.434	4.043	4.543	4.956	1.059
2012	246	4.065	2.833	3.611	4.234	4.654	5.182	0.983
2013	451	4.065	2.890	3.611	4.205	4.745	5.106	1.002
2014	570	3.984	2.740	3.434	4.190	4.654	5.059	1.043
2015	638	3.991	2.708	3.497	4.190	4.727	5.147	1.076
2016	686	3.935	2.708	3.434	4.127	4.635	5.100	1.086

Notes: Panel A of Table 1 reports the distribution and summary statistics of media coverage of ESG incidents (*avg_rri_std*), and of analyst coverage (*lnanacov*), across years. The overall sample consists of 3,097 firm-year observations for 992 U.S. listed companies. The sample period for media coverage of ESG incidents (analyst coverage) ranges from 2007 (2008) to 2015 (2016).

Panel B: The distribution and statistics of *avg_rri_std* and *lnanacov* across industries

Industry (the first two digits of SIC)	*avg_rri_std*							
	N	Mean	10%	25%	Median	75%	90%	Std. div
Oil and gas (13, 29)	125	4.073	0.708	1.165	3.234	5.360	8.301	4.124
Food products (20)	272	3.644	0.591	1.189	2.730	5.376	8.534	3.191
Paper and paper products (24-27)	228	2.581	0.545	0.906	2.013	3.352	5.907	2.192
Chemical products (28)	82	3.168	0.759	1.123	2.208	4.738	6.567	2.655
Manufacturing (30-34)	162	3.743	0.675	1.352	3.278	5.315	7.725	2.801
Computer equipment and services (35, 73)	8	2.400	0.289	0.714	1.794	4.223	5..453	2.054
Electronic equipment (36)	37	3.257	0.587	1.238	2.538	5.004	7.603	2.457
Transportation (37, 39, 40-42, 44, 45)	406	3.613	0.569	1.102	2.836	5.207	7.807	3.256
Scientific instruments (38)	12	1.759	0.344	0.607	1.256	2.947	3.602	1.372
Electric, gas, and sanitary services (49)	44	4.105	1.192	1.604	3.405	5.411	7.631	3.324
Durable goods (50)	37	3.094	0.590	0.876	2.008	4.564	8.125	2.732
Retail (53, 54, 56, 57, 59)	420	2.905	0.471	0.864	2.244	4.118	6.245	2.738
Eating and drinking establishments (58)	21	2.953	0.661	1.139	1.981	3.231	6.454	2.683
Others	1,243	3.540	0.569	1.060	2.496	4.784	7.507	4.283

Industry (the first two digits of SIC)	*lnanacov*							
	N	Mean	10%	25%	Median	75%	90%	Std. div
Oil and gas (13, 29)	125	4.131	3.526	3.871	4.277	4.533	4.762	0.651
Food products (20)	272	3.983	2.890	3.569	4.220	4.575	4.771	0.868
Paper and paper products (24-27)	228	3.948	2.833	3.481	4.103	4.575	4.934	0.910
Chemical products (28)	82	4.137	2.833	3.611	4.263	4.820	5.447	1.038
Manufacturing (30-34)	162	4.201	3.091	3.871	4.394	4.710	5.004	0.745
Computer equipment and services (35, 73)	8	3.846	3.258	3.384	3.785	4.324	4.522	0.515
Electronic equipment (36)	37	4.579	3.871	4.575	4.727	4.920	4.977	0.527
Transportation (37, 39, 40-42, 44, 45)	406	3.662	2.639	3.178	3.761	4.220	4.585	0.885
Scientific instruments (38)	12	3.995	3.584	3.624	3.997	4.394	4.419	0.426
Electric, gas, and sanitary services (49)	44	4.441	3.219	4.174	4.795	4.963	5.268	0.929
Durable goods (50)	37	3.883	2.833	3.332	4.159	4.331	4.615	0.828
Retail (53, 54, 56, 57, 59)	420	3.815	2.639	3.296	3.980	4.560	4.949	0.995
Eating and drinking establishments (58)	21	4.290	2.485	4.522	4.654	4.844	4.852	1.077
Others	1,243	4.067	2.565	3.584	4.290	4.927	5.313	1.212

Notes: Panel B reports the distribution and summary statistics of media coverage of ESG incidents (*avg_rri_std*), and of analyst coverage (*lnanacov*), across industries. The industry classification is based on the first two digits of SIC codes. The overall sample consists of 3,097 firm-year observations for 992 U.S. listed companies, with the sample period ranging from 2007 (2008) to 2015 (2016) for media coverage of ESG incidents (analyst coverage).

Table 2: Summary statistics

Variables	N	Mean	10%	25%	Median	75%	90%	Std. dev.
lnanacov	3,097	3.985	2.773	3.497	4.174	4.673	5.106	1.044
avg_rri_std	3,097	3.410	0.552	1.055	2.494	4.733	7.348	3.578
size	3,097	8.406	6.220	7.318	8.415	9.625	10.532	1.717
idiosynretvol	3,097	0.037	0.017	0.022	0.030	0.045	0.066	0.022
price	3,097	49.614	9.690	19.490	36.760	62.180	95.810	49.944
qtrret	3,097	0.010	-0.365	-0.182	-0.004	0.171	0.376	0.325
roa	3,097	0.033	-0.031	0.010	0.035	0.072	0.118	0.101
finconstraint	3,097	-2481.076	-3339.057	-3328.257	-3316.657	-1467.613	-495.640	1153.740
r&d	3,097	0.027	0	0	0	0	0	0.162
intangible	3,097	0.081	0	0	0	0	0	0.272
btm	3,097	0.648	0.144	0.275	0.486	0.818	1.228	0.614
insti	3,097	2.704	0.139	1.848	2.905	3.709	4.440	1.457
tradingvol	3,097	119.879	3.171	13.412	47.135	134.657	298.800	215.267
regulated	3,097	0.291	0	0	0	1	1	0.454
lyr_esg	3,097	1.363	0	0	1.099	2.079	3.135	1.259
lyr_esg_industry	3,097	4.805	2.485	3.912	4.949	6.265	6.605	1.590
esg_risks_industry	3,097	3.397	1.128	2.164	3.293	4.480	5.365	1.898
error	1,936	0.0086	0.0003	0.0007	0.0018	0.0053	0.0151	0.027
optimism	1,936	0.0033	0	0	0	0.0007	0.0052	0.014
pessimism	1,936	0.0031	0	0	0.0004	0.0020	0.0062	0.010
dispersion	2,043	0.0170	0.0004	0.0010	0.0026	0.0080	0.0232	0.064

Notes: Table 2 reports descriptive statistics of all variables used in the multivariate tests of the relationship of media-covered ESG incidents with analyst coverage and forecasts. All the variables are defined in Appendix 3. The sample period for analyst coverage and forecast properties variables (other variables) spans from 2008 (2007) to 2016 (2015).

Table 3: Multivariate test for the Hypothesis H1

Variables	Dependent variable = $lnanacov_{t+1,i}$
$avg\_rri\_std_{t,i}$	-0.0122***
	(-2.95)
$size_{t,i}$	0.4488***
	(15.81)
$idiosynretvol_{t,i}$	8.7818***
	(6.17)
$price_{t,i}$	-0.0021***
	(-3.58)
$qtrret_{t,i}$	-0.1811***
	(-3.70)
$roa_{t,i}$	-0.1751
	(-0.80)
$finconstraint_{t,i}$	-0.0001***
	(-3.12)
$r\&d_{t,i}$	-0.0770
	(-0.49)
$intangible_{t,i}$	-0.1388
	(-1.50)
$btm_{t,i}$	-0.0588
	(-1.09)
$insti_{t,i}$	0.1267***
	(7.35)
$tradingvol_{t,i}$	-0.0002
	(-1.21)
$regulated_{t,i}$	0.2564
	(0.44)
constant	-1.4490**
	(-2.44)
No. of obs.	3,097
Adj. R^2	0.6376

Notes: Table 3 reports the OLS regression results for the Hypothesis H1. The dependent variable is *lnanacov*. The key independent variable is *avg_rri_std*, capturing the degree of the problem on media-covered ESG incidents. The sample period for *avg_rri_std* and control variables ranges from 2007 to 2015. The definitions of all the variables are provided in Appendix 3. Year and industry dummies are included in the regression, but their results are not reported for the sake of brevity. The industry dummies are constructed based on the first two digits of SIC codes. Among all the continuous independent variables, *size* has the highest VIF value which is 6.57, while all the other VIF values are below 4. The *p*-values in parentheses are based on the standard errors clustered by firm. ***, **, * represent the two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Impact threshold for a confounding variable (ITCV) test for the Hypothesis H1

Variables	(1) ITCV	(2) Implied ITCV correlation	(3) (v, *avg_rri_std*|Z)	(4) (v, *lnanacov*|Z)	(5) *Impact*
avg_rri_std	-0.0186	0.136			
size			0.1842	0.3902	0.0719
price			-0.0603	-0.1227	0.0074
qtrret			-0.0303	-0.0696	0.0021
roa			-0.0422	-0.0123	0.0005
btm			-0.0020	-0.1480	0.0003
regulated			0.0974	-0.0024	-0.0002
r&d			0.0123	-0.0639	-0.0008
intangible			-0.0864	0.0275	-0.0024
idiosynretvol			0.0214	-0.1118	-0.0024
finconstraint			-0.0141	0.2333	-0.0033
tradingvol			-0.0153	0.2408	-0.0037
insti			0.1435	-0.0326	-0.0047

Notes: Table 4 reports the impact threshold for a confounding variable (ITCV) on the baseline regression results, where *lnanacov* (i.e., the variable for analyst coverage) is the dependent variable, and *avg_rri_std* (i.e., the variable for media coverage of CSI) is the key independent variable. The calculation is based on the previous study by Frank (2000). Column (1) reports the impact threshold for a confounding variable and the partial correlation between *avg_rri_std* and the confounding variable that makes the coefficient on *avg_rri_std* statistically insignificant at the 5% level. Column (2) reports the minimum correlation a confounding variable must have between both *lnanacov* and *avg_rri_std* to make the coefficient on *avg_rri_std* statistically insignificant. Column (3) reports the partial Pearson correlation between *avg_rri_std* and each control variable. Column (4) reports the partial Pearson correlation between *lnanacov* and each control variable. Column (5) is the partial impact of each control variable, defined as the product of the correlation between *avg_rri_std* and the control variable and the correlation between *lnanacov* and the control variable.

Table 5: Oster identified sets for the multivariate test for the Hypothesis H1

Dependent variable = *lnanacov*; Key independent variable = *avg_rri_std*			
Oster Conditions	Lower bound (β^*)	Upper bound ($\tilde{\beta}$)	Include zero?
(1) Assume δ=1; R_{max} = min (1.25$\tilde{R}$, 1)	-0.0350	-0.0122	No
(2) Assume δ=1; R_{max} = min (1.5$\tilde{R}$, 1)	-0.0579	-0.0122	No
(3) Assume δ=1; R_{max} = 1	-0.0640	-0.0122	No

Note: Table 5 displays the results of the Oster identified sets for checking the omitted-variable(s) bias for the baseline regression results. The upper bound of the identified set is $\tilde{\beta}$ which is the coefficient on the key independent variable, *avg_rri_std*, of the regression model (1). The lower bound of the identified set is β^*which is derived by using the formula provided by Oster (2019): $\beta^* = \tilde{\beta} - \delta[\dot{\beta} - \tilde{\beta}]\frac{R_{max}-\tilde{R}}{\tilde{R}-\dot{R}}$, where $\tilde{R}$ is the R-square value of the regression model (1); $\dot{\beta}$ is the coefficient on *avg_rri_std* ($\dot{\beta}$ = -0.07081); and $\dot{R}$ is the R-square of the univariate regression without any control variable ($\dot{R}$ = 0.059). Following Oster (2019), we assume that δ = 1 and that R_{max} = 1.25$\tilde{R}$, 1.5$\tilde{R}$, or 1. Row 1 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.25$\tilde{R}$. Row 2 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.5$\tilde{R}$. Row 3 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.

Table 6: Two-stage least squares (2SLS) regression analysis for the Hypothesis H1

Variables	(1) First-stage Dependent variable = $avg\_rri\_std_{t,i}$	(2) Second-stage Dependent variable = $lnanacov_{t+1,i}$
$avg\_rri\_std_{t,i}$		-0.0202**
		(-2.45)
$esg\_risks\_industry_{t,i}$	0.7721***	
	(19.70)	
$lyr\_esg_{t,i}$	0.9969***	
	(10.97)	
$lyr\_esg\_industry_{t,i}$	-0.5331***	
	(-5.54)	
$size_{t,i}$	0.3724***	0.4560***
	(3.95)	(15.27)
$idiosynretvol_{t,i}$	-1.7675	8.7721***
	(-0.56)	(6.26)
$price_{t,i}$	-0.0027	-0.0021***
	(-1.60)	(-3.72)
$qtrret_{t,i}$	-0.2161	-0.1836***
	(-1.35)	(-3.78)
$roa_{t,i}$	-0.9512**	-0.1888
	(-2.16)	(-0.88)
$finconstraint_{t,i}$	0.0002	-0.0001***
	(1.38)	(-3.10)
$r\&d_{t,i}$	0.1947	-0.0684
	(0.52)	(-0.44)
$intangible_{t,i}$	-0.7759***	-0.1479
	(-2.74)	(-1.63)
$btm_{t,i}$	0.2343**	-0.0540
	(2.16)	(-1.01)
$insti_{t,i}$	0.0185	0.1262***
	(0.53)	(7.44)
$tradingvol_{t,i}$	0.0014	-0.0001
	(1.28)	(-1.08)
$regulated_{t,i}$	0.4570	0.2392
	(1.08)	(0.41)
constant	-2.2811***	-1.4854**
	(-3.22)	(-2.47)
No. of obs.	3,097	3,097
Adj. R^2	0.4700	0.6371

Notes: Table 6 reports the results for the two-stage least squares regression for the Hypothesis H1. The first-stage regression is run on the determinants of media-covered CSI (*avg_rri_std)*. The instrument variables are *esg_risks_industry*, *lyr_esg* and *lyr_esg_industry*. The sample period for the independent variables in both the first- and second-stage regressions ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 7: Falsification tests for the Hypothesis H1

Panel A: Subsample regressions on media-covered ESG incidents

Variables	Dependent variables = $lnanacov_{t+1,i}$	
	(1) Low media-covered ESG issues (*avg_rri_std*)	(2) High media-covered ESG issues (*avg_rri_std*)
$avg\_rri\_std_{t,i}$	-0.0221	-0.0118**
	(-0.87)	(-2.47)
$size_{t,i}$	0.5055***	0.3920***
	(12.11)	(11.93)
$idiosynretvol_{t,i}$	9.4025***	6.3852***
	(5.90)	(3.23)
$price_{t,i}$	-0.0029***	-0.0014**
	(-4.30)	(-2.45)
$qtrret_{t,i}$	-0.2968***	-0.0453
	(-4.69)	(-0.69)
$roa_{t,i}$	-0.1478	-0.3739
	(-0.57)	(-1.38)
$finconstraint_{t,i}$	-0.00005	-0.0001***
	(-1.26)	(-2.86)
$r\&d_{t,i}$	-0.2281	0.0717
	(-1.28)	(0.41)
$intangible_{t,i}$	-0.1130	-0.2659**
	(-1.13)	(-2.22)
$btm_{t,i}$	-0.0836	-0.0201
	(-1.17)	(-0.33)
$insti_{t,i}$	0.1093***	0.1361***
	(5.17)	(6.41)
$tradingvol_{t,i}$	0.0003	-0.0001
	(1.02)	(-0.97)
$regulated_{t,i}$	0.9675***	-0.7193**
	(5.88)	(-2.41)
constant	-2.5270***	0.1130
	(-8.19)	(0.42)
No. of obs.	1,548	1,549
Adj. R^2	0.6340	0.6320

Notes: Panel A of Table 7 reports the results of the falsification test of the Hypothesis H1, based on the subsample regressions on media-covered ESG incidents. Column (1) (Column (2)) shows the results of the baseline regression run based on the subsamples of firms that have a low (high) level of media-covered negative ESG issues (*avg_rri_std*). The sample period for the independent variables ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for the sake of brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Panel B: Subsample regressions on the moderating effect of time-series variance of *lnanacov*

Variables	Dependent variables = $lnanacov_{t+1,i}$	
	(1) Low variance of *lnanacov*	(2) High variance of *lnanacov*
$avg\_rri\_std_{t,i}$	-0.0114**	-0.0038
	(-2.43)	(-0.50)
$size_{t,i}$	0.3559***	0.5078***
	(12.42)	(11.52)
$idiosynretvol_{t,i}$	11.1953***	6.8360***
	(5.73)	(3.66)
$price_{t,i}$	-0.0016**	-0.0024***
	(-2.62)	(-2.78)
$qtrret_{t,i}$	-0.0726	-0.2565***
	(-1.05)	(-3.90)
$roa_{t,i}$	0.2049	-0.3914
	(0.65)	(-1.63)
$finconstraint_{t,i}$	-0.0001***	-0.0001
	(-3.32)	(-1.15)
$r\&d_{t,i}$	0.0934	-0.2961
	(0.77)	(-0.94)
$intangible_{t,i}$	-0.2092**	-0.0691
	(-2.46)	(-0.34)
$btm_{t,i}$	-0.0912	-0.0375
	(-1.19)	(-0.59)
$insti_{t,i}$	0.1310***	0.1207***
	(4.55)	(5.47)
$tradingvol_{t,i}$	-0.0000054	0.00004
	(-0.04)	(0.15)
$regulated_{t,i}$	0.5949	-0.0403
	(0.95)	(-0.07)
constant	-0.5460	-1.7679***
	(-0.87)	(-2.62)
No. of obs.	1,527	1,570
Adj. R^2	0.6616	0.6246

Notes: Panel B of Table 7 reports the results for the falsification test of the Hypothesis H1, based on subsample regressions on the moderating effect of time-series variance of *lnanacov*. Column (1) (Column (2)) shows the results of the baseline regression run based on the subsamples of firms that have a low (high) time-series variance of *lnanacov*. The sample period for the independent variables in each regression ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for the sake of brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 8: Heckman two-stage regression analysis for the Hypothesis H1

Variables	(3) First-stage Dependent variable = $ESG\_dummy_{t,i}$	(4) Second-stage Dependent variable = $lnanacov_{t+1,i}$
$avg\_rri\_std_{t,i}$		-0.0073**
		(-2.09)
$competition_{t,i}$	0.2329*	
	(1.82)	
$size_{t,i}$	0.0814**	0.4475***
	(2.23)	(13.57)
$idiosynretvol_{t,i}$	0.8565	9.3074***
	(0.73)	(6.25)
$price_{t,i}$	-0.0001	-0.0021***
	(-0.67)	(-3.47)
$qtrret_{t,i}$	-0.1229**	-0.1838***
	(-2.28)	(-3.53)
$roa_{t,i}$	0.0086	-0.1300
	(0.97)	(-0.61)
$finconstraint_{t,i}$	-0.0002***	-0.0001***
	(-6.24)	(-2.66)
$r\&d_{t,i}$	0.7230***	-0.1223
	(4.41)	(-0.70)
$intangible_{t,i}$	-1.1032**	-0.1372
	(-2.54)	(-1.37)
$btm_{t,i}$	0.0838***	-0.0384
	(2.75)	(-0.76)
$insti_{t,i}$	-0.0160	0.1932***
	(-0.88)	(8.83)
$tradingvol_{t,i}$	0.0041***	-0.0002*
	(7.04)	(-1.75)
$regulated_{t,i}$	-1.7244***	0.1117
	(-2.90)	(0.19)
constant	-1.4048**	-1.475**
	(-2.25)	(-2.30)
imr		-0.0238
		(-0.20)
No. of obs.	5,173	2,817
Adj. R^2	0.2870	0.6619

Notes: Table 8 reports the results of the Heckman two-stage regression for the Hypothesis H1. The first-stage regression is run on the determinants of whether a firm is subject to media coverage of ESG issues (*ESG_dummy*). The sample period for the independent variables in both the first- and second-stage regressions ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 9: Mechanism tests for the Hypothesis H1

Variables	(1) Dependent variable = $stdearnings_{t,i}$	(2) Dependent variable = $lnanacov_{t+1,i}$	(3) Dependent variable = $bidaskspread_{t,i}$	(4) Dependent variable = $lnanacov_{t+1,i}$
$avg\_rri\_std_{t,i}$	0.0357***		0.0001***	
	(3.09)		(4.46)	
$pred\_stdearnings_{t,i}$		-0.3204***		
		(-2.63)		
$pred\_bidaskspread_{t,i}$				-169.4409**
				(-2.40)
$auditfee_{t,i}$			-0.00004	
			(-0.23)	
$salesgrowth_{t,i}$	-0.0605		0.000002	
	(-1.50)		(0.06)	
$size_{t,i}$	0.2402***	0.5466***	-0.0009***	0.3042***
	(4.49)	(10.76)	(-5.21)	(4.85)
$finconstraint_{t,i}$	0.0001***	-0.00005	-0.0000002*	-0.0001***
	(2.72)	(-1.30)	(-1.83)	(-3.60)
$roa_{t,i}$	-0.9028***	-0.4786*	-0.0026*	-0.6001**
	(-4.19)	(-1.89)	(-1.89)	(-2.03)
$insti_{t,i}$	-0.0430***	0.1144***	-0.0004***	0.0762**
	(-3.08)	(5.94)	(-6.76)	(2.51)
$idiosynretvol_{t,i}$		9.9830***		10.0650***
		(6.20)		(5.94)
$price_{t,i}$		-0.0017**		-0.0013*
		(-2.44)		(-1.78)
$qtrret_{t,i}$		-0.2236***		-0.1998***
		(-3.86)		(-3.35)
$r\&d_{t,i}$		-0.3291*		-0.3601*
		(-1.79)		(-1.93)
$intangible_{t,i}$		0.0734		0.0093
		(0.81)		(0.11)
$btm_{t,i}$		-0.0451		0.0006
		(-0.69)		(0.01)
$tradingvol_{t,i}$		-0.0004*		-0.0002
		(-1.91)		(-1.46)
$regulated_{t,i}$		-0.0573		0.1126
		(-0.44)		(0.81)
constant	-1.4656***	-1.0556***	0.0069***	0.6375
	(-4.59)	(-3.16)	(8.17)	(1.25)
No. of obs.	2,377	2,377	2,144	2,144
Adj. R^2	0.2574	0.6519	0.3596	0.6511

Notes: Table 9 reports the results of the mechanism test regarding how media-covered ESG incidents (*avg_rri_std*) impact analyst coverage (*lnanacov*) via increasing the business risk (*stdearnings*) and information risk (*bidaskspread*) of firms. The analysis of the mechanism is done by a two-stage regression. In the first-stage regression, *stdearnings* (*bidaskspread*) is run on *avg_rri_std* as well as a range of control variables. In the second-stage regression, *lnanacov* is run on the fitted value of the first-stage regressions (i.e., *pred_stdearnings* and *pred_bidaskspread*) along with an array of control variables. The sample period for the independent variables in each regression ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for the sake of brevity. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 10: Moderation tests for the Hypothesis H1

Panel A: The moderating effect of industrial product market competition

Variables	Dependent variables = $lnanacov_{t+1,i}$			
	(1) Low product market competition (*substitution*)	(2) High product market competition (*substitution*)	(3) Low product market competition (*mktsize*)	(4) High product market competition (*mktsize*)
$avg\_rri\_std_{t,i}$	-0.0074	-0.0165***	-0.0059	-0.0146***
	(-1.52)	(-2.81)	(-0.93)	(-2.95)
Controls	included	included	included	included
No. of obs.	1,526	1,571	1,551	1,546
Adj. R^2	0.6387	0.6506	0.6325	0.6608

Panel B: The moderating effect of the severity of ESG incidents

Variables	Dependent variable = $lnanacov_{t+1,i}$	
	(1) Low severity of ESG incidents (*severity*)	(2) High severity of ESG incidents (*severity*)
$avg\_rri\_std_{t,i}$	-0.0064	-0.0155***
	(-1.02)	(-3.04)
Controls	Included	Included
No. of obs.	2,057	1,040
Adj. R^2	0.6291	0.6659

Panel C: The moderating effect of analyst sophistication

Variables	Dependent variable = $lnanacov_{t+1,i}$	
	(1) Low analyst sophistication (*bsize_average*)	(2) High analyst sophistication (*bsize_average*)
$avg\_rri\_std_{t,i}$	-0.0123***	-0.0047
	(-2.67)	(-1.31)
Controls	Included	Included
No. of obs.	1,458	1,458
Adj. R^2	0.7263	0.6032

Notes: Table 10 shows the results of the moderating effects of industrial product market competition, the severity of ESG incidents, and the level of analyst sophistication, respectively, on the association between analyst coverage and media-covered ESG incidents. Model (1) is run based on the subsample comprising firms with low (high) values of moderation variables for industrial product market competition, the severity of ESG incidents, and the level of analyst sophistication, respectively. The sample period for the independent variables in each regression ranges from 2007 to 2015. The control variables as well as year and industry dummies for Model (1) are included in each regression, but their results are not reported for the sake of brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 11: Multivariate tests for the Hypothesis H2

Panel A: OLS regression results

Variables	(1) Dependent variable = $error_{t+1,i}$	(2) Dependent variable = $optimism_{t+1,i}$	(3) Dependent variable = $pessimism_{t+1,i}$
$avg\_rri\_std_{t,i}$	0.0006***	0.0002**	0.0002**
	(3.57)	(1.97)	(2.57)
$size_{t,i}$	-0.0047***	-0.0024***	-0.0007
	(-3.11)	(-3.24)	(-1.35)
$price_{t,i}$	0.00004**	0.00002**	-0.000004
	(2.55)	(2.44)	(-0.91)
$qtrret_{t,i}$	-0.0090***	-0.0045***	-0.0009
	(-3.92)	(-3.53)	(-1.09)
$idiosynretvol_{t,i}$	0.2815***	0.0628*	0.0856***
	(4.48)	(1.86)	(3.13)
$intangible_{t,i}$	0.0025	-0.0009	0.0027*
	(1.03)	(-0.64)	(1.87)
$tradingvol_{t,i}$	0.000007	0.000004*	-0.0000001
	(1.07)	(1.90)	(-0.05)
$insti_{t,i}$	-0.0032***	-0.0012***	-0.0008***
	(-4.58)	(-3.48)	(-3.21)
$btm_{t,i}$	0.0013	-0.0011	0.0021**
	(0.42)	(-0.74)	(2.05)
$roa_{t,i}$	-0.0437***	-0.0165*	-0.0091*
	(-2.64)	(-1.80)	(-1.78)
$finconstraint_{t,i}$	-0.000003***	-0.000001**	-0.000001*
	(-2.85)	(-2.03)	(-1.65)
$horizon_{t,i}$	0.0082***	0.0032***	0.0015*
	(4.04)	(2.96)	(1.95)
$change\_roa_{t,i}$	-0.0063	0.0088	-0.0052
	(-0.33)	(0.82)	(-0.73)
$change\_eps_{t,i}$	0.0146	-0.0075	0.0078*
	(1.04)	(-0.87)	(1.77)
$surprise_{t,i}$	-0.0003	-0.0015***	0.0009**
	(-0.26)	(-2.64)	(2.45)
$gexp\_average_{t,i}$	0.0002	0.0001	0.00002
	(0.84)	(0.89)	(0.30)
$bsize\_average_{t,i}$	-0.00002	-0.00003	0.00001
	(-0.51)	(-1.00)	(0.49)
constant	-0.0153	0.0013	-0.0014
	(-0.92)	(0.17)	(-0.23)
No. of obs.	1,936	1,936	1,936
Adj. R^2	0.3342	0.2161	0.2054

Notes: Panel A reports the results of the OLS regression of analyst forecast error, forecast optimism, and forecast pessimism on media-covered ESG incidents. The dependent variables are analyst forecast error (*error*), forecast optimism (*optimism*), forecast pessimism (*pessimism*), respectively. The key independent variable is *avg_rri_std*, capturing the degree of the problem on media-covered ESG incidents. The sample period for the independent variables in each regression ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for brevity. The industry dummies are constructed based on the first two digits of SIC codes. Among all the continuous independent variables, *size* has the highest VIF values which are 9.40, 7.85, and 9.40 for the regressions of forecast error, forecast optimism, and forecast pessimism, respectively, while all the other VIF values are below 4. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Panel B: Mechanism Tests for the Hypothesis H2

Variables	(1) Dependent variable = *stdearnings*$_{t,i}$	(2) Dependent variable = *error*$_{t+1,i}$	(3) Dependent variable = *bidaskspread*$_{t,i}$	(4) Dependent variable = *error*$_{t+1,i}$
avg_rri_std$_{t,i}$	0.0286***		0.00005***	
	(3.54)		(3.48)	
pred_stdearnings1$_{t,i}$		0.0140**		
		(1.97)		
pred_bidaskspread1$_{t,i}$				15.1283***
				(3.36)
auditfee$_{t,i}$			-0.00002	
			(-0.18)	
salesgrowth$_{t,i}$	-0.0602		0.00002	
	(-1.43)		(0.34)	
size$_{t,i}$	0.2683***	-0.0088***	-0.0005***	0.0026
	(3.77)	(-3.67)	(-4.99)	(1.25)
finconstraint$_{t,i}$	0.0001**	-0.00001***	-0.0000001	-0.000003**
	(2.38)	(-3.42)	(-0.93)	(-2.43)
roa$_{t,i}$	-0.9972***	-0.0265	-0.0016*	-0.0167
	(-4.40)	(-1.26)	(-1.66)	(-1.09)
insti$_{t,i}$	-0.0498***	-0.0023***	-0.0003***	0.0008
	(-3.29)	(-3.27)	(-5.56)	(0.63)
idiosynretvol$_{t,i}$		0.2855***		0.3111***
		(4.29)		(4.30)
price$_{t,i}$		0.00004***		0.00003**
		(2.62)		(2.21)
qtrret$_{t,i}$		-0.0091***		-0.0090***
		(-3.90)		(-3.66)
intangible$_{t,i}$		0.0038		0.0042
		(1.27)		(1.25)
btm$_{t,i}$		0.0003		0.00003
		(0.19)		(0.03)
tradingvol$_{t,i}$		0.00001*		0.000001
		(1.90)		(1.56)
horizon$_{t,i}$		0.0079***		0.0092***
		(3.73)		(3.89)
change_roa$_{t,i}$		-0.0072		-0.0057
		(-0.37)		(-0.30)
change_eps$_{t,i}$		0.0167		0.0179
		(1.14)		(1.20)
surprise$_{t,i}$		-0.0008		-0.0009
		(-0.71)		(-0.77)
gexp_average$_{t,i}$		0.0001		0.0003
		(0.56)		(1.46)
bsize_average$_{t,i}$		-0.000005		-0.000005
		(-0.10)		(-0.08)
constant	-1.4080***	0.0096	0.0062***	-0.1130***
	(-3.88)	(0.48)	(8.36)	(-3.43)
No. of obs.	1,922	1,922	1,732	1,732
Adj. R^2	0.2521	0.3191	0.3689	0.3386

Notes: Panel B reports the results for the mechanism test regarding how media-covered ESG incidents (*avg_rri_std*) impact analyst forecast error (*error*) via increasing the business risk (*stdearnings*) and information risk (*bidaskspread*) of firms. The analysis of the mechanism is done by a two-stage regression. In the first-stage regression, *stdearnings* (*bidaskspread*) is run on *avg_rri_std* as well as a range of control variables. In the second-stage regression, *error* is run on the fitted value of the first-stage regressions (i.e., *pred_stdearnings1* and *pred_stdbidaskspread1*) along with an array of control variables. Year and industry dummies are included in each regression, but their results are not reported for the sake of brevity. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 12: Multivariate tests for the Hypothesis H3

Panel A: OLS regression results

Variables	Dependent variable = $dispersion_{t+1,i}$
$avg\_rri\_std_{t,i}$	0.0015***
	(3.93)
$size_{t,i}$	-0.0068**
	(-2.13)
$price_{t,i}$	0.00003
	(1.21)
$qtrret_{t,i}$	-0.0274***
	(-4.92)
$idiosynretvol_{t,i}$	0.9386***
	(6.88)
$intangible_{t,i}$	0.0042
	(0.66)
$tradingvol_{t,i}$	0.00001
	(0.36)
$insti_{t,i}$	-0.0078***
	(-4.11)
$finconstraint_{t,i}$	-0.00001**
	(-2.59)
$horizon_{t,i}$	0.0205***
	(3.48)
$change\_roa_{t,i}$	0.0001
	(0.00)
$change\_eps_{t,i}$	-0.0358
	(-1.17)
$surprise\_prioreps_{t,i}$	0.0041
	(0.59)
$gexp\_avg_{t,i}$	0.0003
	(0.52)
$bsize\_avg_{t,i}$	-0.00002
	(-0.14)
constant	-0.0752*
	(-1.76)
No. of obs.	2,043
Adj. R^2	0.3319

Notes: Panel A reports the result of the OLS regression of analyst forecast dispersion on media-covered ESG incidents. The dependent variable is analyst forecast dispersion (namely, *dispersion*). The key independent variable is *avg_rri_std*, capturing the degree of the problem on media-covered ESG incidents. The sample period for the independent variables in the regression ranges from 2007 to 2015. Year and industry dummies are included in the regression, but their results are not reported for the sake of brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. Among all the independent variables, *size* has the highest VIF value which is 7.51, while all the other VIF values are below 4. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Panel B: Mechanism tests for the Hypothesis H3

Variables	(1) Dependent variable = *stdearnings*$_{t,i}$	(2) Dependent variable = *dispersion*$_{t+1,i}$	(3) Dependent variable = *bidaskspread*$_{t,i}$	(4) Dependent variable = *dispersion*$_{t+1,i}$
avg_rri_std$_{t,i}$	0.0236***		0.0001***	
	(3.43)		(3.96)	
pred_stdearnings2$_{t,i}$		0.0925***		
		(4.21)		
pred_bidaskspread2$_{t,i}$				39.8092***
				(3.48)
auditfee$_{t,i}$			0.0001	
			(0.72)	
salesgrowth$_{t,i}$	-0.2249***		0.00003	
	(-3.35)		(0.43)	
roa$_{t,i}$	-0.5792***		-0.00001	
	(-4.38)		(-0.84)	
size$_{t,i}$	0.1774***	-0.0240***	-0.0005***	0.0123**
	(6.33)	(-4.33)	(-6.75)	(2.43)
finconstraint$_{t,i}$	0.0001***	-0.00001***	-0.00000004	-0.00001**
	(2.62)	(-4.61)	(-0.60)	(-3.08)
insti$_{t,i}$	-0.0371***	-0.0032**	-0.0003***	0.0036
	(-3.89)	(-2.31)	(-6.23)	(1.29)
idiosynretvol$_{t,i}$		0.9479***		1.0665***
		(6.25)		(6.34)
price$_{t,i}$		0.0001**		0.00004
		(2.59)		(1.37)
qtrret$_{t,i}$		-0.0260***		-0.0277***
		(-4.55)		(-4.44)
intangible$_{t,i}$		0.0095		0.0102
		(1.07)		(1.01)
tradingvol$_{t,i}$		0.00001		0.00001
		(0.53)		(0.73)
horizon$_{t,i}$		0.0206***		0.0221***
		(3.66)		(3.66)
change_roa$_{t,i}$		0.0375		-0.0086
		(0.78)		(-0.17)
change_eps$_{t,i}$		-0.0307		-0.0300
		(-1.03)		(-0.93)
surprise$_{t,i}$		0.0055		0.0060
		(0.80)		(0.79)
gexp_average$_{t,i}$		0.0003		0.0004
		(0.40)		(0.61)
bsize_average$_{t,i}$		0.00001		0.00004
		(0.12)		(0.33)
constant	-1.0409***	0.0178	0.0051***	-0.2970***
	(-6.30)	(0.41)	(11.51)	(-3.97)
No. of obs.	2,028	2,028	1,831	1,831
Adj. R^2	0.3746	0.3471	0.3716	0.3441

Notes: Panel B reports the results for the mechanism test regarding how media-covered ESG incidents (*avg_rri_std*) impact analyst forecast dispersion (*dispersion*) via increasing the business risk (*stdearnings*) and information risk (*bidaskspread*) of firms. The analysis of the mechanism is done by a two-stage regression. In the first-stage regression, *stdearnings* (*bidaskspread*) is run on *avg_rri_std* as well as a range of control variables. In the second-stage regression, *dispersion* is run on the fitted value of the first-stage regressions (i.e., *pred_stdearnings2* and *pred_bidaskspread2*) along with an array of control variables. The sample period for the independent variables in each regression ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for sake of brevity. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Online Appendix

In this Online Appendix for the paper, titled "*Does media coverage of firms' environment, social, and governance (ESG) incidents affect analyst coverage and forecasts? A risk perspective*", we offer supplementary results on the association between media coverage of ESG incidents and the error and dispersion of analyst forecasts. Specifically, we check the robustness of our main findings to potential endogeneity and sample selection bias, and present the results for the robustness tests in Tables A1 and A2.

Table A1: Robustness check for the Hypothesis H2

Panel A: Results for the impact threshold for a confounding variable (ITCV) test

Variables	(1) ITCV	(2) Implied ITCV correlation	(3) (v, *avg_rri_std*|Z)	(4) (v, *error*|Z)	(5) *Impact*
avg_rri_std	0.0387	0.197			
roa			-0.0582	-0.1387	0.0081
tradingvol			0.1041	0.0367	0.0038
btm			0.0928	0.0348	0.0032
insti			-0.0155	-0.1705	0.0026
qtrret			-0.0191	-0.1383	0.0026
change_eps			0.0449	0.0518	0.0023
gexp_average			0.0339	0.0395	0.0013
intangible			-0.0672	-0.0184	0.0012
surprise			-0.0334	-0.0250	0.0008
finconstraint			-0.0061	-0.0884	0.0005
change_roa			-0.0127	-0.0071	0.0001
bsize_average			0.0164	-0.0178	-0.0003
price			-0.0672	0.0557	-0.0037
idiosynretvol			-0.0245	0.2222	-0.0054
horizon			-0.1427	0.0860	-0.0123
size			0.1515	-0.0949	-0.0144

Notes: Panel A of Table A1 reports the results for the impact threshold for a confounding variable (ITCV) for the regression results, where *error* is the dependent variable, and *avg_rri_std* is the key independent variable. The calculation is based on the previous study by Frank (2000). Column (1) reports the impact threshold for a confounding variable and the partial correlation between *avg_rri_std* and the confounding variable that makes the coefficient on *avg_rri_std* statistically insignificant at the 5% level. Column (2) reports the minimum correlation a confounding variable must have with both *error* and *avg_rri_std* to make the coefficient on *avg_rri_std* statistically insignificant. Column (3) reports the partial Pearson correlation between *avg_rri_std* and each control variable. Column (4) reports the partial Pearson correlation between *error* and each control variable. Column (5) is the partial impact of each control variable, defined as the product of the correlation between *avg_rri_std* and the control variable and the correlation between *error* and the control variable.

Panel B: Oster identified sets

Dependent variable = *error*; Key independent variable = *avg_rri_std*			
Oster Conditions	Lower bound ($\tilde{\beta}$)	Upper bound (β^{*})	Include zero?
(1) Assume δ=1; R_{max} = min (1.25$\tilde{R}$, 1)	0.0006	0.0008	No
(1) Assume δ=1; R_{max} = min (1.5$\tilde{R}$, 1)	0.0006	0.0011	No
(2) Assume δ=1; R_{max} = 1	0.0006	0.0025	No

Note: Panel B displays the results of the Oster identified sets for checking the omitted-variable(s) bias for the regression results, where *error* is the dependent variable, and *avg_rri_std* is the key independent variable. The lower bound of the identified set is $\tilde{\beta}$ which is the coefficient on the key independent variable, *avg_rri_std*, of the regression model (6). The upper bound of the identified set is β^{*}which is derived by using the formula provided by Oster (2019): $\beta^{*} = \tilde{\beta} - \delta[\dot{\beta} - \tilde{\beta}]\frac{R_{max}-\tilde{R}}{\tilde{R}-\dot{R}}$, where $\tilde{R}$ is the R-square value of the regression model (6); $\dot{\beta}$ is the coefficient on *avg_rri_std* ($\dot{\beta}$ = -0.00036); and $\dot{R}$ is the R-square of the univariate regression without any control variable ($\dot{R}$ = 0.002). Following Oster (2019), we assume that δ = 1 and R_{max} = 1.25$\tilde{R}$, 1.5$\tilde{R}$, or 1. Row 1 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.25$\tilde{R}$. Row 2 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.5$\tilde{R}$. Row 3 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.

Panel C: Two-stage least square (2SLS) regression results

Variables	(1) First-stage Dependent variable = $avg\_rri\_std_{t,i}$	(2) Second-stage Dependent variable = $error_{t+1,i}$
$avg\_rri\_std_{t,i}$		0.0007***
		(2.60)
$esg\_risks\_industry_{t,i}$	0.7803***	
	(19.87)	
$lyr\_esg_{t,i}$	0.8969***	
	(10.18)	
$lyr\_esg\_industry_{t,i}$	-0.4794***	
	(-3.93)	
$size_{t,i}$	0.2222**	-0.0048***
	(2.07)	(-3.24)
$price_{t,i}$	-0.0028	0.00004***
	(-1.62)	(2.61)
$qtrret_{t,i}$	-0.0667	-0.0090***
	(-0.42)	(-4.00)
$idiosynretvol_{t,i}$	-1.3317	0.2817***
	(-0.47)	(4.60)
$intangible_{t,i}$	-0.5612**	0.0026
	(-2.20)	(1.07)
$tradingvol_{t,i}$	0.0012	0.00001
	(1.20)	(1.05)
$insti_{t,i}$	0.0573	-0.0031***
	(1.36)	(-4.68)
$btm_{t,i}$	0.1388	0.0012
	(0.96)	(0.42)
$roa_{t,i}$	-0.9708	-0.0435***
	(-1.28)	(-2.69)
$finconstraint_{t,i}$	-0.0001	-0.000003***
	(-0.58)	(-2.91)
$horizon_{t,i}$	-0.5879***	0.0083***
	(-2.76)	(4.16)
$change\_roa_{t,i}$	-1.1942	-0.0061
	(-1.13)	(-0.33)
$change\_eps_{t,i}$	1.2491**	0.0145
	(2.39)	(1.06)
$surprise_{t,i}$	-0.0440	-0.0003
	(-0.96)	(-0.26)
$gexp\_average_{t,i}$	-0.0030	-0.00002
	(-1.04)	(-0.53)
$bsize\_average_{t,i}$	-0.0017	0.0002
	(-0.11)	(0.85)
constant	1.2023	-0.0156
	(0.88)	(-0.96)
No. of obs.	1,936	1,936
Adj. R^2	0.5087	0.3341

Notes: Panel C reports the results for the two-stage least squares regression for the test of the association between analyst forecast error (*error*) and media-covered ESG incidents. The first-stage regression is run on the determinants of media-covered CSI (*avg_rri_std*). The instrument variables are *esg_risks_industry*, *lyr_esg*, and *lyr_esg_industry*. The sample period for the independent variables in both the first- and second-stage regressions ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Panel D: Heckman two-stage regression results

Variables	(3) First-stage Dependent variable = $ESG\_dummy_{t,i}$	(4) Second-stage Dependent variable = $error_{t+1,i}$
$avg\_rri\_std_{t,i}$		0.0004**
		(2.43)
$competition_{t,i}$	-0.2473	
	(-0.76)	
$size_{t,i}$	0.0079	-0.0036**
	(0.15)	(-2.40)
$price_{t,i}$	-0.0017**	0.00003**
	(-2.26)	(2.15)
$qtrret_{t,i}$	-0.1090**	-0.0060***
	(-2.05)	(-3.02)
$idiosynretvol_{t,i}$	2.2025	0.1702***
	(1.40)	(2.83)
$intangible_{t,i}$	-0.3467	0.0016
	(-0.70)	(0.60)
$tradingvol_{t,i}$	0.0047***	0.000009
	(6.65)	(1.61)
$insti_{t,i}$	0.0144	-0.0021***
	(0.60)	(-3.31)
$btm_{t,i}$	0.0904*	0.0057*
	(1.67)	(1.79)
$roa_{t,i}$	0.1631	-0.0316*
	(0.97)	(-1.91)
$finconstraint_{t,i}$	-0.0003***	-0.000002*
	(-5.93)	(-1.87)
$horizon_{t,i}$	-0.0786	0.0056***
	(-0.95)	(2.76)
$change\_roa_{t,i}$	0.0394***	-0.0193
	(3.42)	(-1.31)
$change\_eps_{t,i}$	0.0718	0.0193
	(0.75)	(1.56)
$surprise_{t,i}$	-0.0172**	0.00003
	(-2.06)	(0.03)
$gexp\_average_{t,i}$	0.0145*	0.0001
	(1.91)	(0.22)
$bsize\_average_{t,i}$	0.0035**	-0.000003
	(2.30)	(-0.10)
constant	4.187***	-0.0078
	(6.11)	(-0.38)
imr_t		0.0028
		(0.46)
No. of obs.	3,026	1,791
Adj. R^2	0.2754	0.2965

Notes: Panel D reports the results for the Heckman two-stage regression for the test of the association between analyst forecast error (*error*) and media-covered ESG incidents. The first-stage regression is run on the determinants of whether a firm is subject to media coverage of ESG issues (*ESG_dummy*). The sample period for the independent variables in both the first- and second-stage regressions ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table A2: Robustness check for the Hypothesis H3

Panel A: Results for the impact threshold for a confounding variable (ITCV) test

Variables	(1) ITCV	(2) Implied ITCV correlation	(3) (v, *avg_rri_std*|Z)	(4) (v, *dispersion*|Z)	(5) *Impact*
avg_rri_std	0.0462	0.215			
qtrret			-0.0414	-0.1782	0.0074
finconstraint			-0.0578	-0.0904	0.0052
insti			-0.0204	-0.1689	0.0034
intangible			-0.0637	-0.0412	0.0026
tradingvol			0.1294	0.0134	0.0017
idiosynretvol			0.0020	0.3196	0.0006
change_roa			-0.0386	-0.0106	0.0004
surprise_prioreps			-0.0059	0.0223	-0.0001
bsize_average			0.0236	-0.0034	-0.0001
gexp_average			0.0362	-0.0049	-0.0002
price			-0.0808	0.0180	-0.0015
change_eps			0.0323	-0.0758	-0.0024
size			0.1107	-0.0485	-0.0054
horizon			-0.1465	0.0886	-0.0130

Notes: Panel A of Table A2 presents the results of the impact threshold for a confounding variable (ITCV) for the regression results, where *dispersion* is the dependent variable, and *avg_rri_std* is the key independent variable. The calculation is based on the previous study by Frank (2000). Column (1) reports the impact threshold for a confounding variable and the partial correlation between *avg_rri_std* and the confounding variable that makes the coefficient on *avg_rri_std* statistically insignificant at the 5% level. Column (2) reports the minimum correlation a confounding variable must have with both *dispersion* and *avg_rri_std* to make the coefficient on *avg_rri_std* statistically insignificant. Column (3) reports the partial Pearson correlation between *avg_rri_std* and each control variable. Column (4) reports the partial Pearson correlation between *dispersion* and each control variable. Column (5) is the partial impact of each control variable, defined as the product of the correlation between *avg_rri_std* and the control variable and the correlation between *dispersion* and the control variable.

Panel B: Oster identified sets

Dependent variable = *dispersion*; Key independent variable = *avg_rri_std*			
Oster Conditions	Lower bound ($\tilde{\beta}$)	Upper bound (β^{*})	Include zero?
(1) Assume δ=1; R_{max} = min (1.25$\tilde{R}$, 1)	0.0015	0.0019	No
(1) Assume δ=1; R_{max} = min (1.5$\tilde{R}$, 1)	0.0015	0.0024	No
(2) Assume δ=1; R_{max} = 1	0.0015	0.0050	No

Note: Panel B displays the results of the Oster identified sets for checking the omitted-variable(s) bias for the regression results, where *dispersion* is the dependent variable, and *avg_rri_std* is the key independent variable. The lower bound of the identified set is $\tilde{\beta}$ which is the coefficient on the key independent variable, *avg_rri_std*, of the regression model (7). The upper bound of the identified set is β^{*}which is derived by using the formula provided by Oster (2019): $\beta^{*} = \tilde{\beta} - \delta[\dot{\beta} - \tilde{\beta}]\frac{R_{max}-\tilde{R}}{\tilde{R}-\dot{R}}$, where $\tilde{R}$ is the R-square value of the regression model (7); $\dot{\beta}$ is the coefficient on *avg_rri_std* ($\dot{\beta}$ = -0.00024); and $\dot{R}$ is the R-square of the univariate regression without any control variable ($\dot{R}$ = 0.0002). Following Oster (2019), we assume that δ = 1 and R_{max} = 1.25$\tilde{R}$, 1.5$\tilde{R}$, or 1. Row 1 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.25$\tilde{R}$. Row 2 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.5$\tilde{R}$. Row 3 reports the results of the identified set under the assumption that δ=1 and R_{max} = 1.

Panel C: Two-stage least square (2SLS) regression results

Variables	(1) First-stage Dependent variable = $avg\_rri\_std_{t,i}$	(2) Second-stage Dependent variable = $dispersion_{t+1,i}$
$avg\_rri\_std_{t,i}$		0.0018**
		(2.95)
$esg\_risks\_industry_{t,i}$	0.7888***	
	(18.40)	
$lyr\_esg_{t,i}$	0.9170***	
	(10.40)	
$lyr\_esg\_industry_{t,i}$	-0.4640***	
	(-3.55)	
$size_{t,i}$	0.1401*	-0.0069**
	(1.66)	(-2.18)
$price_{t,i}$	-0.0031*	0.00003
	(-1.85)	(1.28)
$qtrret_{t,i}$	-0.1321	-0.0273***
	(-0.86)	(-5.03)
$idiosynretvol_{t,i}$	-0.6180	0.9384***
	(-0.26)	(7.03)
$intangible_{t,i}$	-0.2977	0.0043
	(-1.10)	(0.68)
$tradingvol_{t,i}$	0.0014	0.000004
	(1.53)	(0.30)
$insti_{t,i}$	0.0471	-0.0078***
	(1.16)	(-4.19)
$finconstraint_{t,i}$	-0.0001	-0.00001***
	(-1.15)	(-2.65)
$horizon_{t,i}$	-0.5740***	0.0208***
	(-2.85)	(3.64)
$change\_roa_{t,i}$	-1.0987*	0.0006
	(-1.93)	(0.01)
$change\_eps_{t,i}$	0.7312**	-0.0360
	(2.20)	(-1.20)
$surprise\_prioreps_{t,i}$	-0.0799	0.0041
	(-0.61)	(0.60)
$gexp\_average_{t,i}$	-0.0049	0.0003
	(-0.32)	(0.52)
$bsize\_average_{t,i}$	-0.0032	-0.00002
	(-1.19)	(-0.15)
constant	1.5727	-0.0763*
	(1.18)	(-1.84)
No. of obs.	2,043	2,043
Adj. R^2	0.5127	0.3318

Notes: Panel C reports the results for the two-stage least squares regression for the test of the association between analyst forecast dispersion (*dispersion*) and media-covered ESG incidents. The first-stage regression is run on the determinants of media-covered CSI (*avg_rri_std*). The instrument variables are *esg_risks_industry*, *lyr_esg*, and *lyr_esg_industry*. The sample period for the independent variables in both the first- and second-stage regressions ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Panel D: Heckman two-stage regression results

Variables	(1) First-stage Dependent variable = $ESG\_dummy_{t,i}$	(2) Second-stage Dependent variable = $dispersion_{t+1,i}$
$avg\_rri\_std_{t,i}$		0.0007**
		(2.54)
$competition_{t,i}$	-0.1507***	
	(-0.52)	
$size_{t,i}$	0.0162	-0.0061**
	(0.35)	(-2.06)
$price_{t,i}$	-0.0014*	0.00001
	(-1.87)	(0.34)
$qtrret_{t,i}$	-0.1089**	-0.0178***
	(-2.12)	(-3.72)
$idiosynretvol_{t,i}$	2.6682*	0.5931***
	(1.82)	(4.90)
$intangible_{t,i}$	-0.4134	0.0003
	(-0.89)	(0.08)
$tradingvol_{t,i}$	0.0039***	0.00001
	(5.78)	(0.79)
$insti_{t,i}$	-0.0041	-0.0028**
	(-0.18)	(-2.49)
$finconstraint_{t,i}$	-0.0003***	-0.00001*
	(-7.54)	(-1.77)
$horizon_{t,i}$	-0.0411	0.0128***
	(-0.52)	(2.76)
$change\_roa_{t,i}$	0.0236	0.0022
	(1.39)	(1.02)
$change\_eps_{t,i}$	0.0516	-0.0106
	(0.58)	(-0.59)
$surprise\_prioreps_{t,i}$	-0.0011	-0.0016
	(-0.08)	(-0.25)
$gexp\_average_{t,i}$	0.0163***	0.0002
	(2.24)	(0.49)
$bsize\_average_{t,i}$	0.0020	0.0001
	(1.36)	(1.05)
constant	2.6726***	-0.0403
	(4.25)	(-1.55)
imr_t		-0.0061
		(-0.66)
No. of obs.	3,282	1,871
Adj. R^2	0.2823	0.2476

Notes: Panel D reports the results for the Heckman two-stage least regression for the test of the association between analyst forecast dispersion (*dispersion*) and media-covered ESG incidents. The first-stage regression is run on the determinants of whether a firm is subject to media coverage of ESG issues (*ESG_dummy*). The sample period for the independent variables in both the first- and second-stage regressions ranges from 2007 to 2015. Year and industry dummies are included in each regression, but their results are not reported for brevity. The industry dummies are constructed based on the first two digits of SIC codes. The *p*-values in parentheses are based on the standard errors clustered by firm. All the variables are defined in Appendix 3. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.