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

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Abstract: Media coverage of environment, social and governance (ESG) issues provides useful information for analysts as corporate social irresponsibility events potentially influence firm performance and risk. Our study explores whether and how analysts respond to media coverage of corporate social irresponsibility by examining its relationship with analyst coverage and forecasts. We find 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 high business risk, high information opacity, and more intense industrial product market competition. We also find a positive association between media-covered ESG incidents and analyst forecast error and dispersion, suggesting that analysts might fail to incorporate the ESG risk exposures into their forecasts in an appropriate manner. Overall, our results suggest that corporate social irresponsibility undermines the role analysts play as information intermediaries for investors in the stock market.

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 and criticism of corporate social irresponsibility (hereafter, CSI) from investors, regulators, and other interest groups. Environmental, social and governance (hereafter, ESG) incidents, which are three dominating concerns towards CSI,[1] impair the public's trust in the offending firms and adversely impact their operation and financial stability.[2] 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 protest from customers and other stakeholders, caused a huge amount 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 capital market effects.

To explore the market consequences of CSI, we focus on the negative ESG incidents covered by the media for three reasons.[3] First, unlike information about corporate social responsibility (henceforth, CSR) which is often self-disclosed originally by firms, CSI-related information is commonly covered by the media. Managers generally have a tendency to withhold bad news (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). Thereby, the economic consequences of CSI to a firm depend crucially on how well the CSI is known to widespread stakeholders. The media can serve this end well by revealing and

[1] Typical examples of ESG incidents can be found via Factset (http://insight.factset.com/resources /at-a-glance-reprisk-data-feed), and are summarized in Appendix 1.

[2] Throughout this paper, we refer to stakeholders in a narrow term as non-shareholder stakeholders, which are exclusive of shareholders.

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

disseminating CSI-related information to a wide variety of stakeholders. [4]

Second, humans are normally more attentive to negative information than the positive one (Rozin and 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; Kolbel et al., 2017), but also gives the media a high motive to report ESG incidents to cater to the stakeholders' and public's information needs. The coverage of negative ESG issues helps the media increase the amount of views, subscriptions, and thus revenues to a substantial extent.

Third, although existing studies document the positive impact of CSR on corporate performance (Brown and Dacin, 1997; Roberts and Dowling, 2002; Lev et al., 2010; Dhaliwal et al., 2011; Edmans, 2011; Goss and Roberts, 2011), far less attention has been given to the market consequences of CSI behavior, as reflected by ESG incidents. Nonetheless, increasing evidence (e.g., Kang et al., 2016; Lenz et al., 2017; Oikonomou et al., 2014; Raghunandan and Rajgopal 2021) shows that CSI and CSR co-exist. Specifically, a firm that engages actively in CSR activities can be socially irresponsible in some aspect. For instance, in September 2015, the U.S. Environmental Protection Agency (EPA) accused the German automaker, Volkswagen Group, of cheating on the emissions test by installing a 'defeat device' in diesel engines to deflate the reported level of excessive carbon-dioxide emission. Ironically, in the same month when this news was covered, Volkswagen claimed itself as a 'corporate citizen' and advocated its social and ecological commitments on its website (Riera and Iborra, 2017). This implies that a firm might

[4] The economic impacts of the CSI-related media coverage on firms are realized via the media diffusing CSI and tainting the firm's reputation among its business stakeholders. Since our study concerns how the media-covered CSI affects analysts through its economic consequences on firms, it is less important for us to identify and analyze whether the media unmasks and creates the original information about negative ESG incidents or merely rebroadcasts the existing information uncovered by others.

engage in CSI and CSR simultaneously. We focus on studying CSI as it concerns market participants more than CSR based on the extant literature (e.g., Hawn 2021; Li et al., 2021).[5] 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 examining the stock market consequences of CSI.

Analysts play an important role as information intermediaries in the stock market by helping investors better understand a firms' risk, performance, and future prospect. Hence their responses to media coverage of the negative ESG incidents are of great significance for understanding the market consequences of CSI. Yet this issue has received little research attention thus far. To fill the research gap, we investigate how media coverage of ESG incidents influences analyst coverage and forecast properties.

Media coverage of ESG incidents brings about reputational losses and legal fines to a firm (Karpoff et al., 2008; Philippe and Durand, 2011; Lin et al., 2016). 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 have a propensity to implement strategic changes, which adds further uncertainty to future firm performance, and meanwhile, to withhold other potential corporate bad news, which leads to high information opacity of the firm. The uncertain future performance and the opaque information environment together increase the difficulty and costs for analysts to provide accurate earnings forecasts. On the other hand, as a firm

[5] Not all firms afford to be socially responsible based on their capacities and available resources. For instance, the costs of pursuing CSR activities are likely to be higher than the associated benefits for financially constrained firms or start-up companies. However, in line with legal and ethical norms, all firms should avoid taking socially irresponsible actions to others. Therefore, market participants generally attach more importance to CSI than CSR. Hawn (2021) provides evidence that media coverage of CSR has no impact on the firms' cross-border acquisitions, while media coverage of CSI impedes the completion of such acquisitions. Li et al. (2021) find that the practice of providing CSR disclosures in the management discussion and analysis (MD&A) section of annual reports does not increase the value of firms with good CSR performance, but does decrease the value of firms with high CSR concerns.

subject to media coverage of ESG incidents is likely to 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. Therefore, we expect that media coverage of ESG incidents lowers analyst coverage.

We use 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 that consists of 3,095 firm-year observations for 992 U.S. listed companies, we find that analyst coverage is negatively associated with media coverage of ESG incidents. This finding is robust to using the impact threshold for a confounding variable (ITCV) test, a two-stage least squares (2SLS) regression, and a falsification test to control for potential endogeneity, and is stronger for firms that face higher business risk, higher information risk, and more intense industrial product market competition. Furthermore, we find that media coverage of ESG incidents increases forecast error and forecast dispersion of analysts. This finding is also amenable to employing the ITCV test and 2SLS regression to mitigate potential endogeneity bias. The analyst coverage and forecasts which are about a firm's earnings rather than CSI is unlikely to reversely affect the media coverage which concerns the ESG incidents. Or rather, when deciding whether and how to cover negative ESG incidents of a firm, the media normally would not refer to analyst coverage of the earnings of the firm. Therefore, our analysis should, by nature, be subject little to reverse causality issues. Our robustness checks for endogeneity are consistent with this notion.

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 and Lundholm, 1996; Barth et al., 2001; Simpson 2010; Dhaliwal et al., 2012; He et al., 2019b) 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 media.[6] We fill this gap in the literature. 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., 2019b). As the real economic consequences that media coverage of CSI would have on firms are highly uncertain by nature, whether analysts are sophisticated enough in properly processing the information about the media-covered CSI is an open question that warrants an empirical analysis. Our findings suggest that analysts lack such sophistication.

Second, 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. We show that such media coverage of CSI undermines analysts' information intermediary role in terms of reduced analyst coverage, increased forecast error, and enlarged forecast dispersion. This flags concerns about potentially decreased market efficiency and underscores the importance of curbing CSI and improving analyst performance in forecasting.

Last, but not least, Dhaliwal et al. (2012) find that CSR, which is self-disclosed by firms, reduces analyst forecast error. This finding, however, does not necessarily imply a positive association between CSI and analyst forecast error, as recent studies (Kang et al., 2016; Lenz et al., 2017; Oikonomou et al., 2014; Chen et al., 2020) show the coexistence of CSR and CSI, which

[6] Bradshaw et al. (2021) examine how analysts revise their earnings forecasts in response to the soft covered by 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 the 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 real economic consequences of the media coverage on firms.

are hard to disentangle in the financial reports by firms. Moreover, CSR is not necessarily value-relevant to shareholders, especially in cases when there are conflicts of interests between stakeholders and shareholders; by contrast, CSI is likely to be value-relevant, as it plausibly harms, and increases the uncertainty of, future firm performance. Since CSR and media-covered CSI have substantively different economic impacts on firms, the inferences in Dhaliwal et al. (2012) cannot be used in an opposite manner to draw inferences on the impact of media-covered CSI on analyst coverage and forecasts. Another difference between Dhaliwal et al. (2012) and our study is that we also look at analyst coverage and forecast dispersion when examining how CSI influences analyst decisions.

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 the main variables. Section 4 presents our research design and discusses the empirical results. Section 5 conducts further empirical analysis. Section 6 concludes.

2. Literature Review and Hypothesis Development

2.1 Media Coverage of ESG Incidents and Analyst Coverage

Firms have been criticized for their socially irresponsible behavior as exemplified by environmental pollutions, safety violations, and hazardous products, etc. These concerns towards CSI lie mainly in environmental, social, and governance (ESG) incidents that arise in a firm. Once these incidents are realized by its stakeholders, the firm will likely be subject to their boycotts and/or sanctions. Media is an important channel to reveal and disseminate ESG incidents to a wide range of stakeholders, inducing the public’s awareness of CSI behavior (Deephouse, 2000). The ESG incidents, however, are less likely to be self-disclosed by a firm. Therefore, media coverage of ESG incidents provides a reasonable setting in which to examine the capital market effects of CSI. Given the role analysts play as information intermediaries in the stock market, examining their responses to media coverage of ESG incidents should advance our understanding of the market consequences of CSI.

Media coverage of ESG incidents may influence the performance and risks of a firm in various ways. First, ESG incidents tarnish a firm's reputation and impair stakeholders' trust in the firm. Economic theory (Klein and 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 and Shanley, 1990; Fombrun, 1996; Hansen et al., 2011; Cao et al., 2015). 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 and Webb, 2005; Braunsberger and 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, media coverage of ESG incidents 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 substantive 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 widespread audience, criticism and stigmatization from the public will run against the firm, resulting in its loss of reputation (Wiesenfeld et al., 2008). To recoup the reputational losses and allay the threat of litigation, the firm has an incentive to change its business strategies in response to the negative media coverage, thereby signaling to the public that the ESG issue is being resolved. 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 for purposes of increasing its competitive advantage, would lead to uncertain firm performance.

Besides, a firm of which ESG incidents are broadcasted by the media may withhold other corporate bad news, or even window-dress earnings performance, to prevent corporate reputation from deteriorating and to mitigate potential negative consequences of media-covered CSI. This likely behavior increases the information opacity of the firm.

Taken together, 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. Forecast accuracy is a key determinant factor for an analyst's remuneration and career prospect (e.g., Clarke and Subramanian, 2006; Marinelli and Weissensteiner, 2014). To maintain the accuracy of forecasts for firms that confront media coverage of ESG incidents, analysts have to exert more effort and incur more costs for acquiring and processing value-relevant information. 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 are likely to have less interest in investments in stocks of a firm that is subject to media coverage of ESG incidents and associated reputational losses, as such stocks tend to have higher risks and lower returns (Cox et al., 2004; Johnson and Greening, 1999; Graves and Waddock, 1994). 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 and 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. Based on the above discussion over the supply of, and demand for, analyst services, we make the following hypothesis:

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

Firms with high business risk are typically featured by high volatility of net operating income. Thus, high corporate business risk makes it more difficult for analysts to forecast earnings for firms that are subject to the negative media-covered ESG incidents. To provide accurate earnings forecasts for firms that have high levels of inherent business risk and of media-covered ESG concerns, analysts would have to incur even higher information acquisition and/or procession costs for the forecasting. On this basis, we propose the following hypothesis:

H1a: The negative association between analyst coverage and media-covered ESG incidents is more pronounced for firms with high business risk.

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 of such firms. In the context of media coverage of ESG issues, high information opacity further increases the difficulty in providing an accurate forecast of a firm. In specific, 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. Therefore, we make the following hypothesis:

H1b: The negative association between analyst coverage and media-covered ESG incidents is more pronounced for firms with high information opacity.

When the overall market demand for a certain type of product is substantially lower than those suppliable 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 have a higher risk of consumer switching and associated higher uncertainty of strategy implementation and sale performance; also, they might have stronger incentives to withhold various other bad news, or mask firm performance, to maintain customers as well as external funders. As such, information risk and business risk would both be likely to be higher for firms confronting the fierce product market competition and media coverage of CSI; it would therefore be more difficult for analysts to cover such firms. This reasoning leads to the following hypothesis:

H1c: The negative association between analyst coverage and media-covered ESG incidents is more pronounced for firms confronted with intense industrial product market competition.

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 is gathered from Factset. Other data are taken from CRSP and Compustat. Subject to the data availability on RepRisk, our sample covers the years 2007-2015.[7] We require that all firm-year observations have the necessary data required to construct variables of interest for our regression analyses. This gives us 3,095 firm-year observations for 992 unique firms for testing the association between analyst coverage and media coverage of ESG incidents.

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 reach of information sources, severity of incidents and criticism, and 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 on a firm's ESG incidents covered by the media. RRI is recalculated when there is new news about a firm,

[7] Our university only subscribed the RepRisk data that span only the years 2007-2015. Besides, in an un-tabulated analysis, we exclude the financial crisis period 2007-2009, and still find 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.

and decays to 0 over a maximum period of two years if no new criticism is captured.

We use the RepRisk data, rather than the MSCI ESG Research (previously known as KLD) data, for our study 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). 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.[8] A higher value of *avg_rri_std* represents a greater level of problems on 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 associated with analyst coverage, we employ the following ordinary least squares (OLS) regression model:

[8] 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.

$$
\begin{aligned}
lnanacov_{t+1} = {} & \alpha_0 + \alpha_1 avg\_rri\_std_t + \alpha_2 size_t + \alpha_3 retvol_t + \alpha_4 stdearnings_t + \alpha_5 price_t \\
& + \alpha_6 qtrret_t + \alpha_7 roa_t + \alpha_8 finconstraint_t + \alpha_9 r\&d_t + \alpha_{10} intangible_t + \alpha_{11} btm_t \\
& + \alpha_{12} insti_t + \alpha_{13} tradingvol_t + \alpha_{14} regulated_t + \alpha_{15} year\_dummy \\
& + \alpha_{16} industry\_dummy + \varepsilon_t
\end{aligned} \tag{1}
$$

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., 2019a). The key independent variable, *avg_rri_std*, and control variables are measured at fiscal year t. The hypothesis H1 predicts that the coefficient of *avg_rri_std* is negative and statistically significant at a conventional level.

To mitigate potential correlated-omitted-variable(s) bias, Model (1) includes a host of control variables that are found by previous research to be correlated with analyst coverage. Analysts are prone to forecast earnings for larger firms, as higher profits likely earned from investing in larger firms increase investors' demand for analysts covering such firms (Bhushan, 1989). Therefore, we include firm size (*size*) as a control variable and predict it to be positively associated with analyst coverage. Bhushan (1989) also points out that high firm-specific uncertainty increases investors' demand for analyst services and thus motivates analysts to follow firms with higher uncertainty. We use two proxies, return volatility (*retvol*) and earnings volatility (*stdearnings*), to proxy for firm-specific uncertainty, which is expected to be positively related to analyst coverage.

Brennan and Hughes (1991) claim that firms with high abnormal stock returns are less attractive to analysts. Two explanations may justify analysts' preference of following firms with low abnormal stock returns: First, firms with high abnormal stock returns are normally considered to be overvalued. Analysts tend to avoid making forecasts for such firms, as issuing negative recommendations may prevent analysts from getting private information from managers (Siconolfi, 1995). Moreover, issuing a negative report may negatively affect potential investment banking business and reduce trading commissions (Darlin, 1983). Second, analysts believe that, for firms experiencing price appreciation, the primary sources of value have been largely dug out, leaving limited space for exploiting a new source of value for such firms. Therefore, following Brennan and Hughes (1991), we control for the share price (*price*) and abnormal stock returns (*qtrret*) in Model (1). Because analysts are prone to make forecasts for well-performing and financially healthy firms (Das et al., 2006; Lee and So, 2017), we also control for return on assets (*roa*) and financial constraints (*finconstraint*) in the regression.

Information environment of firms is another critical factor impacting analyst coverage, as the richness of firms' information environment increases the net benefits of analyst forecasts and thereby attracts analyst coverage (Lang and Lundholm, 1996). We include three proxies for information asymmetry, namely, research and development expenses (*r&d*), intangible assets (*intangible*), and book-to-market ratio (*btm*), as per prior research (e.g., Aboody and Lev, 2000; Lev, 2001; Barth et al., 2001; Huddart and Ke, 2007). Because institutional investors often have high demand for analyst services (Bhushan, 1989; O'Brien and Bhushan, 1990; Frankel et al., 2006), we include institutional stock ownership (*insti*) as a control variable. Commission fees paid to analysts are determined by trading volume, so analysts are likely to follow firms with high trading volume. Therefore, we control for trading volume (*tradingvol*). Industrial regulatory status (*regulated*) is also included in the regression because analysts are prone to cover firms that are in more regulated industries (O'Brien and Bhushan, 1990). The definitions of all the variables are given in Appendix 3. 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; Kolbel et al., 2017). Therefore, we include industry and year dummies in Model (1). We do not control for firm-fixed effects in the regression as they are multicollinear with industry dummies.[9]

[Insert Table 1 here]

Table 2 reports descriptive statistics of *avg_rri_std* as well as other variables used in our multivariate tests. All continuous variables are winsorized at the 1 and 99 percentage points, respectively, to alleviate potential outlier problems.

[Insert Table 2 here]

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, supporting the hypothesis H1 --- that analyst coverage is negatively associated with media coverage of ESG incidents.[10] A one-standard-deviation increase in *avg_rri_std* induces a decrease in *lnanacov* by 0.0426, which accounts for around 1.1% of the full-sample mean of *lnanacov*.[11] 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 8.64, are below 4, suggesting that our regression model is free from multicollinearity issues.

[Insert Table 3 here]

[9] The firm-fixed-effects regression assumes that both 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. We rely mainly on the cross-sectional variances in the two variables to test the hypothesis H1.

[10] 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, which supports the hypothesis H1.

[11] *avg_rri_std* has been scaled by the standard deviation of monthly RRI scores for a year and thus lacks time-series variance. This is probably a reason for why the economic significance of the coefficient on *avg_rri_std* seems small.

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 (Frank, 2000; Larcker and Rusticus, 2010) to apply the impact threshold for a confounding variable method (ITCV) for our baseline multivariate 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 is, the less likely our regression results are subject to potential correlated-omitted-variable(s) bias.

[Insert Table 4 here]

Table 4 presents the results of the ITCV test for the baseline regression analysis. The estimated absolute value of ITCV is 0.0209, which is higher than any absolute value of the impact factor (*Impact*) of variables (except for *size*) controlled in Model (1). As the 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 as well as of other control variables. We may rest assured that our baseline regression results are reasonably amenable to accounting for the potential correlated-omitted variable(s).

Another endogeneity that might bias our baseline results is reverse causality. To ease this concern, we perform a two-stage least squares (2SLS) regression analysis. As the calculation of RRI accounts for the value and intensity of news, we believe that either the firm-specific or industry-level news count on ESG issues (namely, *lyr_esg* and *lyr_esg_industry*, respectively) is related to *avg_rri_std*, but the news count *per se* should have little association with analyst forecast behavior.[12] Or rather, given the effect of media coverage of ESG incidents that 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. Therefore, we use *lyr_esg* and *lyr_esg_industry* as instrumental variables in the 2SLS regression model. 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.

[Insert Table 5 here]

Table 5 reports the two-stage regression results. For the first step, both *lyr_esg* and *lyr_esg_industry* have a statistically significant relationship with *avg_rri_std*. A one-standard-deviation increase in *lyr_esg* (*lyr_esg_industry*) is associated with a rise (decrease) in *avg_rri_std* by 1.472 (0.759), which is equivalent to 43.18% (22.27%) of the full-sample mean 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 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 206.611. This figure is far above the cut-off point of 11.59, below which two 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. This suggests that our baseline regression results are robust to correcting for the potential reverse causality. The Hansen J statistic is 1.533, indicating that overidentifying restrictions are valid for our 2SLS regression.

Our baseline regression results might also be subject to dynamic endogeneity. In specific,

[12] The Spearman correlation between *avg_rri_std* and *lyr_esg* (*lyr_esg_industry*), not tabulated for parsimony, amounts to 0.5719 (0.1686), suggesting that *avg_rri_std* is not multicollinear with *lyr_esg* (*lyr_esg_industry*).

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 rule out this possibility, we conduct a falsification test. We run Model (1) based on two subsamples, respectively, which are partitioned by the full-sample median of the time-series variance of *lnanacov* (namely, *stdlnanacov*). If the dynamic endogeneity alternatively explained our baseline results, we should find the coefficient of *avg_rri_std* to be significantly more negative in the subsample that has higher time-series variance in *lnanacov*. However, as shown in Table 6, 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. This result confutes the possibility that our baseline regression results are driven by the dynamic endogeneity. As a matter of fact, the decision of the media to cover negative ESG incidents of a firm are unlikely to be driven by analyst coverage and forecasts that relate to a firm's projected earnings performance rather than CSI itself. Thus, the dynamic endogeneity that is attributed to the reverse causality is less of a concern in our study.

[Insert Table 6 here]

4.2 Multivariate Test of the Hypotheses H1a, H1b, and H1c

To test the hypotheses H1a, H1b, and H1c, we divide our full sample into two subsamples based on the median of business risk, information opacity, and industrial product market competition, respectively, and run Model (1) for each subsample. Earnings volatility (*stdearnings*) is used as the proxy for business risk. A larger value of *stdearnings* represents a higher business risk of a firm. Table 7 reports the results of the subsample regressions for the moderating effect of business risk. The coefficient of *avg_rri_std* for the high-business-risk subsample is negative and statistically significant at the 5% level, whereas the coefficient on *avg_rri_std* for the low-business-risk subsample is not statistically significant. This result is therefore consistent with the hypothesis H1a.

[Insert Table 7 here]

Following Hutton et al. (2009), we measure information opacity by the three-year moving sum of the absolute value of annual abnormal accruals (*opacity*). A larger value of *opacity* indicates higher information opacity of a firm. Table 8 displays the results of the moderating effect of information opacity. The coefficient of *avg_rri_std* is negatively and statistically significant at the 5% level for the high-information-opacity subsample, but the one in the low-information-opacity subsample is not statistically significant. Thus, the hypothesis H1b is buttressed.

[Insert Table 8 here]

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. Panels A and B of Table 9 provide the regression results obtained from using *substitution* and *mktsize*, respectively, as the proxies for product market competition. In both panels, 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. This result thus supports the hypothesis H1c.

[Insert Table 9 here]

5. Further Tests

5.1 The Association between Analyst Forecast Error and Media-covered ESG Incidents

Given the negative association of media-covered ESG incidents with analyst coverage, we further investigate whether media coverage of ESG incidents affects analyst forecast error. As discussed in Section 2.1, firms with ESG incidents covered by the media tend to have high business risk and high information risk. It is thus difficult for analysts to make an accurate forecast for such firms. Thus, we predict that analyst forecast error is positively correlated with media coverage of ESG incidents. To test this prediction, we specify the following OLS regression model:

$$
\begin{aligned}
error_{t+1} = \alpha_0 &+ \alpha_1 avg\_rri\_std_t + \alpha_2 size_t + \alpha_3 price_t + \alpha_4 qtrret_t + \alpha_5 retvol_t + \alpha_6 intangible_t \\
&+ \alpha_7 tradingvol_t + \alpha_8 insti_t + \alpha_9 btm_t + \alpha_{10} roa_t + \alpha_{11} finconstraint_t \\
&+ \alpha_{12} horizon_t + \alpha_{13} change\_roa_t + \alpha_{14} surprise_t + \alpha_{15} change\_eps_t \\
&+ \alpha_{16} gexp\_average + \alpha_{17} bsize\_average + \alpha_{18} year\_dummy \\
&+ \alpha_{19} industry\_dummy + \varepsilon_t
\end{aligned} \tag{2}
$$

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 of the analysts' last forecasts of annual EPS (e.g., He et al., 2020). In line with prior studies (e.g., Lang and Lundholm, 1996; Clement, 1999; Ali et al., 2007; Tan et al., 2011; Dhaliwal et al., 2012), a range of control variables are included: firm size (*size*), stock price (*price*), abnormal stock returns (*qtrret*), return volatility (*retvol*), intangible assets (*intangible*), trading volume (*tradingvol*), institutional stock ownership (*insti*), 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*), earnings surprise (*surprise*), change in earnings per share (*change_eps*), 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 detail in Appendix 3. Industry and year dummies are also controlled in the regression.

[Insert Table 10 here]

Panel A of Table 10 presents 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 an increase in *error* by 0.21 percentage points, which is equivalent to 24.96% of the full-sample mean of *error*. We also conduct an ITCV test to mitigate the concern of correlated-omitted-variable(s) bias potentially arising in the regression estimation, and report the ITCV results in Panel B. The absolute value of ITCV is 0.0357, which is higher than any absolute value of the impact factor (*Impact*) of variables controlled in Model (2). From this, we can infer that our results in Panel A are not driven by potential correlated-omitted-variable(s). Although reverse causality is 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 such a plausible endogeneity concern. Panel C reports the 2SLS regression results. The second-stage regression results are qualitatively the same as those in Panel A, 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.

In addition, we also 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 (2) with *optimism* and *pessimism*, respectively, for the regression estimation. *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 a firm's EPS is higher than the analyst's last forecast of 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 a firm's actual EPS is lower than the analyst's last EPS forecast. The average is taken of *optimism* and *pessimism* if multiple analysts make the forecasts of EPS for a firm for fiscal year t+1.

Table 11 reports the regression results. The coefficients on *avg_rri_std* are positively and statistically significant for both the *optimism* regression and *pessimism* regression. A one-standard-deviation increase in *avg_rri_std* causes an increase in *optimism (pessimism)* by 0.07 (0.07) percentage points, which is equivalent to 21.68% (23.08%) of the full-sample mean of *optimism* (*pessimism*). 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.

[Insert Table 11 here]

5.2 The Association between Analyst Forecast Dispersion and Media-covered ESG Incidents

Apart from analyst forecast error, forecast dispersion may also be influenced by media coverage of CSI. It is noteworthy that an increase in analyst forecast error does not necessarily denote an increase 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 increased information risk and increased business risk due to media-covered ESG incidents would increase the variance in forecast inputs and parameters used by different analysts, thereby enlarging the divergence in their forecasts.

Analysts are different in sophistication, knowledge, and professionalism (Fang and Yasuda, 2014). Previous studies (Hunton and McEwen, 1997; Sidhu and 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 a firm subject to media-covered ESG incidents, more able analysts should maintain forecast accuracy better than others, thus causing an increased dispersion in analysts' forecasts.

Furthermore, different analysts may hold different sets of value-relevant information or put different weights on diverse information used in forecasting (Lang and Lundholm, 1996). 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.

On the other hand, given the difficulty in accurately forecasting earnings of firms that are subject to media coverage of ESG incidents, analysts might be sluggish in making their own forecasts and instead mimic the forecasts made by other analysts. Such analysts' mimicking behavior would lead to lower dispersion in analysts' earnings forecasts. To test whether and how analyst forecast dispersion is correlated with media coverage of ESG incidents, we use the following OLS regression model:

$$
\begin{aligned}
dispersion_{t+1} = {} & \alpha_0 + \alpha_1 avg\_rri\_std_t + \alpha_2 size_t + \alpha_3 price_t + \alpha_4 qtrret_t + \alpha_5 retvol_t \\
& + \alpha_6 intangible_t + \alpha_7 tradingvol_t + \alpha_8 insti_t + \alpha_9 btm_t + \alpha_{10} ro\alpha_t \\
& + \alpha_{11} finconstraint_t + \alpha_{12} horizon_t + \alpha_{13} change\_roa_t + \alpha_{14} suprise\_prioreps_t \\
& + \alpha_{15} change\_eps_t + \alpha_{16} gexp\_average + \alpha_{17} bsize\_average + \alpha_{18} year\_dummy \\
& + \alpha_{19} industry\_dummy + \varepsilon_t
\end{aligned} \tag{3}
$$

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 are at least three analysts that forecast EPS for a firm for the fiscal year. Following previous studies (e.g., Bhushan, 1989; Brennan and Hughes, 1991; Lang and Lundholm, 1996; Hunton and McEwen, 1997; Jacob et al., 1999; Das et al., 2006; Sidhu and Tan, 2011; Lee and So, 2017), we control for a broad set of variables in Model (3): firm size (*size*), stock price (*price*), abnormal stock returns (*qtrret*), return volatility (*retvol*), intangible assets (*intangible*), trading volume (*tradingvol*), institutional stock ownership (*insti*), 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*), earnings surprise (*surprise_prioreps*), change in earnings per share (*change_eps*), 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 detailed definition in Appendix 3. We also control for industry and year dummies in the regression.

[Insert Table 12 here]

Table 12 Panel A shows the results of OLS regression from running Model (3). 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 an increase in *dispersion* by 0.21 percentage points, which is equivalent to 17.89% of the full-sample mean of *dispersion*. We also conduct the ITCV test and the 2SLS regression model, similar to what we do previously, to allay the potential concern of correlated-omitted-variable(s) bias and reverse causality. As suggested by the results of the ITCV test (2SLS regression) in Panel B (Panel C), our regression results for Model (3) are robust to controlling for the potential endogeneity.

6 Conclusion

Corporate social irresponsibility (CSI) could trigger serious adverse economic and social consequences on firms by blemishing firms' reputation, impairing the trust of stakeholders towards firms, and increasing relevant firm risks. On the other hand, the market consequences and value impacts of CSI depend on how well CSI is known to widespread stakeholders. Media plays a crucial role in broadcasting CSI behavior to a wide range of stakeholders. Furthermore, CSI and CSR may coexist in the sense that firms claiming themselves socially responsible may commit CSI (e.g., Kang et al., 2016; Lenz et al., 2017; Oikonomou et al., 2014; Chen et al., 2020). Therefore, we utilize media coverage of ESG incidents as the proxy for CSI, and examine how financial analysts, the critical information intermediaries in the financial marketplace, respond to the media-covered ESG incidents.

Based on a sample of U.S. listed companies, we find that media-covered ESG incidents is associated with reduced analyst coverage. The result persists after controlling for potential endogeneity problems and is more pronounced for firms with higher business risk, higher information opacity, and more intense industrial product market competition. We also find evidence to suggest that analyst forecasts are adversely affected by media-covered ESG incidents. In particular, the error and dispersion of analyst forecasts increase substantially as a result of media coverage of ESG incidents. The reduced analyst coverage, along with the increased forecast error and forecast dispersion, implies the undermining of analysts' role as information intermediaries and plausible consequential reduction in the capital market efficiency. These thus underline the importance for regulators and board of directors to curb CSI, and for analysts to improve performance in the forecasting for socially irresponsible firms, particularly those that are subject to media coverage of ESG incidents.

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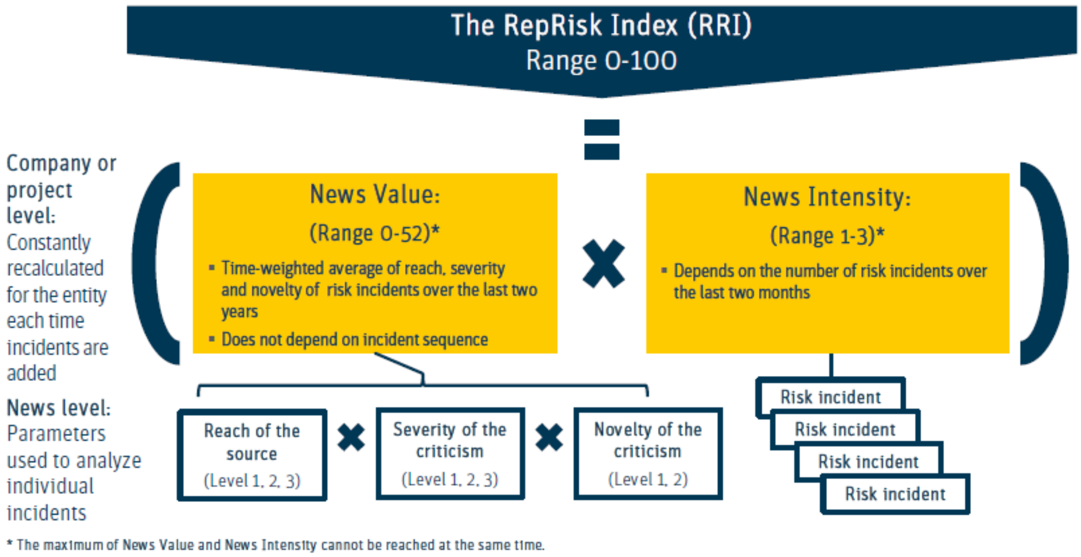
Appendix 1: Research scope of RepRisk database

Environmental issues	Social issues	Governance issues
Animal mistreatment Climate changes, GHG 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, 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 scores in a fiscal year, scaled by the standard deviation of monthly RRI scores.
size	The natural logarithm of the market value of a firm's equity at the end of a fiscal year.
retvol	The standard deviation of daily size-adjusted abnormal returns for a fiscal year.
stdearnings	The deciles rank of earnings volatility, which is computed as the standard deviation of net income before extraordinary items in the current and previous four years.
price	The stock price of a firm at the fiscal year-end date.
qtrret	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. SA index is re-scaled by dividing 1,000. hp is winsorized at the 1% and 99% levels, respectively.
r&d	1 if the research and development expense of a firm is positive for a fiscal year, and 0 otherwise.
intangible	Intangible assets divided by total assets for a firm at the end of a fiscal year.
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) codes 4900-4999, 6000-6411, and 6500-6999), and 0 otherwise.
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 2-digit SIC industry in a fiscal year.
opacity	the three-year moving sum of the absolute value of annual abnormal accruals developed by Hutton et al. (2009).
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).
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. *error* is winsorized at the 1% and 99% levels, respectively.
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.
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.
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.
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. *optimism* is winsorized at the 1% and 99% levels, respectively.
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.
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. *pessimism* is winsorized at the 1% and 99% levels, respectively.
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*, we require that there are at least three analysts who forecast annual EPS for a firm for the fiscal year. *dispersion* is winsorized at the 1% and 99% levels, respectively.
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.

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	119	2.655	0.710	1.024	2.195	3.604	5.510	2.052
2009	145	2.830	0.610	1.055	2.177	3.599	6.460	2.274
2010	169	2.469	0.402	0.7589	1.575	3.3	5.499	2.426
2011	246	2.954	0.5	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	569	3.208	0.592	0.931	2.437	4.655	6.834	3.129
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	119	3.985	2.708	3.401	4.111	4.595	5.182	0.901
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	569	3.983	2.708	3.434	4.190	4.654	5.063	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 3,095 firm-year observations for 992 U.S. listed companies. The sample period for the 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)	405	3.605	0.569	1.102	2.834	5.197	7.807	3.257
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	1,242	3.541	0.569	1.060	2.477	4.784	7.507	4.284

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)	405	3.659	2.639	3.178	3.761	4.220	4.575	0.884
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	1,242	4.068	2.639	3.584	4.290	4.927	5.313	1.211

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 3,095 firm-year observations for 992 U.S. listed companies, with the sample period for the media coverage of ESG incidents (analyst coverage) ranging from 2007 (2008) to 2015 (2016).

Table 2: Summary statistics

Variables	N	Mean	10%	25%	Median	75%	90%	Std. dev
lnanacov	3,095	3.985	2.773	3.497	4.174	4.673	5.106	1.044
avg_rri_std	3,095	3.409	0.552	1.047	2.486	4.734	7.348	3.578
size	3,095	8.407	6.222	7.318	8.415	9.625	10.532	1.715
retvol	3,095	0.0219	0.011	0.0137	0.0183	0.0264	0.038	0.012
stdearnings	3,095	6.4126	2	4	7	9	10	2.736
price	3,095	49.63	9.7	19.49	36.76	62.19	95.81	49.95
qtrret	3,095	0.0100	-0.365	-0.182	-0.00429	0.171	0.376	0.324
roa	3,095	0.0341	-0.031	0.01000	0.0356	0.0724	0.118	0.085
finconstraint	3,095	-2481	-3339.1	-3328	-3317	-1468	-495.6	1154
r&d	3,095	0.0268	0	0	0	0	0	0.162
intangible	3,095	0.00895	0	0	0	0	0	0.044
btm	3,095	0.647	0.144	0.275	0.485	0.818	1.227	0.609
insti	3,095	2.701	0.155	1.849	2.906	3.711	4.440	1.445
tradingvol	3,095	115.4	3.174	13.41	47.13	134.7	298.78	181.6
regulated	3,095	0.291	0	0	0	1	1	0.454
lyr_esg	3,095	1.363	0	0	1.099	2.079	3.135	1.259
lyr_esg_industry	3,095	4.085	2.485	3.892	4.949	6.265	6.605	1.591
error	1,945	0.0086	0.0003	0.0007	0.0018	0.0052	0.015	0.027
optimism	1,945	0.0033	0	0	0	0.0007	0.0052	0.014
pessimism	1,945	0.0031	0	0	0.0004	0.0020	0.0061	0.010
dispersion	1,978	0.0120	0.0004	0.0009	0.0025	0.0077	0.0211	0.036

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

Table 3: Multivariate test of the hypothesis H1

Variables	Dependent variable = $lnanacov_{t+1}$
$avg\_rri\_std_t$	-0.0119***
	(-3.07)
$size_t$	0.4416***
	(13.42)
$retvol_t$	16.4108***
	(5.28)
$stdearnings_t$	0.0320***
	(3.28)
$price_t$	-0.0019***
	(-3.22)
$qtrret_t$	-0.1911***
	(-3.90)
roa_t	-0.1612
	(-0.68)
$finconstraint_t$	-0.00005
	(-1.60)
$r\&d_t$	-0.1008
	(-0.71)
$intangible_t$	-0.5241
	(-1.55)
btm_t	-0.0695
	(-1.24)
$insti_t$	0.1272***
	(7.20)
$tradingvol_t$	-0.0004**
	(-2.24)
$regulated_t$	0.2123
	(0.38)
constant	-1.4965***
	(-2.61)
No. of obs.	3,095
Adj. R^2	0.6396

Notes: Tables 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 regressions but 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 8.64, while all the other VIF values are below 4. The *p*-values in parentheses are based on the standard errors clustered by firm. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), 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	-0.0209	0.145			
size			0.1071	0.3209	0.0344
stdearnings			0.0636	0.0994	0.0063
price			-0.0510	0.1037	0.0053
qtrret			-0.0222	-0.0724	0.0016
regulated			-0.0086	-0.1357	0.0012
r&d			-0.0113	-0.0482	0.0005
roa			-0.0421	-0.0116	0.0005
intangible			-0.0271	-0.0159	0.0004
insti			-0.0035	0.2353	-0.0008
btm			0.0826	-0.0190	-0.0016
finconstraint			0.0343	-0.0756	-0.0026
tradingvol			0.1687	-0.0458	-0.0077
retvol			-0.0705	0.2199	-0.0155

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 a 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: Two-stage least squares regression analysis of the hypothesis H1

Variables	(1) First-stage Dependent variable = $avg\_rri\_std_t$	(2) Second-stage Dependent variable = $lnanacov_{t+1}$
$avg\_rri\_std_t$		-0.0276**
		(-2.01)
lyr_esg_t	1.1693***	
	(12.78)	
$lyr\_esg\_industry_t$	-0.4771***	
	(-4.15)	
$size_t$	0.2691***	0.4513***
	(2.98)	(13.35)
$retvol_t$	-10.3200	16.2117***
	(-1.60)	(5.27)
$stdearnings_t$	0.0594**	0.0340***
	(1.99)	(3.48)
$price_t$	-0.0012	-0.0019***
	(-0.73)	(-3.44)
$qtrret_t$	-0.0053	-0.1941***
	(-0.03)	(-4.00)
roa_t	-1.3469**	-0.1887
	(-2.48)	(-0.81)
$finconstraint_t$	0.0001	-0.00005
	(1.07)	(-1.49)
$r\&d_t$	-0.0410	-0.0955
	(-0.08)	(-0.68)
$intangible_t$	0.3028	-0.5361
	(0.14)	(-1.60)
btm_t	0.2121*	-0.0621
	(1.85)	(-1.11)
$insti_t$	0.0268	0.1267***
	(0.76)	(7.27)
$tradingvol_t$	0.0023*	-0.0003*
	(1.90)	(-1.79)
$regulated_t$	-0.0954	0.1780
	(-0.14)	(0.31)
constant	-1.2567	-1.5445***
	(-1.39)	(-2.62)
No. of obs.	3,095	3,095
Adj. R^2	0.3577	0.6375

Notes: Table 5 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 *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 the regressions but 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 level (two-tailed), respectively.

Table 6: Falsification test of the hypothesis H1

Variables	Dependent variables = $lnanacov_{t+1}$	
	(1) Low variance of *lnanacov*	(2) High variance of *lnanacov*
$avg\_rri\_std_t$	-0.0106**	-0.0063
	(-2.35)	(-0.83)
$size_t$	0.3715***	0.4765***
	(10.15)	(9.89)
$retvol_t$	21.4608***	12.5512***
	(6.09)	(2.93)
$stdearnings_t$	0.0148	0.0405***
	(1.23)	(2.87)
$price_t$	-0.0015**	-0.0023***
	(-2.46)	(-2.64)
$qtrret_t$	-0.0825	-0.2570***
	(-1.21)	(-3.90)
roa_t	0.0891	-0.2936
	(0.27)	(-1.02)
$finconstraint_t$	-0.0001**	-0.00001
	(-2.28)	(-0.25)
$r\&d_t$	0.0047	-0.3276
	(0.05)	(-1.25)
$intangible_t$	-0.3238	-0.2577
	(-0.88)	(-0.43)
btm_t	-0.1028	-0.0542
	(-1.34)	(-0.82)
$insti_t$	0.1239***	0.1289***
	(4.25)	(5.53)
$tradingvol_t$	-0.0002	2.95e-06
	(-1.14)	(0.01)
$regulated_t$	0.5951	-0.0686
	(1.00)	(-0.12)
constant	-0.7961	-1.6601**
	(-1.33)	(-2.56)
No. of obs.	1,526	1,569
Adj. R^2	0.6582	0.6274

Notes: Table 6 reports the results for the falsification test of the hypothesis H1. Column (1) (Column (2)) shows the result of the baseline regression run based on the subsample of the low (high) variance of $lnanacov_{t-1}$. The sample period for the independent variables in the regressions ranges from 2007 to 2015. Year and industry dummies are included in the regressions but not reported for 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 level (two-tailed), respectively.

Table 7: Multivariate test of the hypothesis H1a

Variables	Dependent variables = $lnanacov_{t+1}$	
	(1) Low business risk (*stdearnings*)	(2) High business risk (*stdearnings*)
$avg\_rri\_std_t$	-0.0120	-0.0088**
	(-1.52)	(-2.05)
$size_t$	0.5432***	0.3106***
	(11.04)	(7.5)
$retvol_t$	10.7549**	14.0059***
	(2.43)	(3.51)
$stdearnings_t$	0.0462***	0.0305
	(2.90)	(1.31)
$price_t$	-0.0032***	-0.0010*
	(-4.10)	(-1.86)
$qtrret_t$	-0.2042***	-0.1486**
	(-3.01)	(-2.15)
roa_t	-0.3103	-0.2730
	(-1.00)	(-1.10)
$finconstraint_t$	0.00003	-0.00005
	(0.62)	(-0.98)
$r\&d_t$	-0.3454	-0.1083
	(-1.27)	(-0.86)
$intangible_t$	-0.4313	-0.1203
	(-0.57)	(-0.35)
btm_t	-0.0206	-0.0847
	(-0.26)	(-1.27)
$insti_t$	0.1052***	0.1198***
	(4.28)	(5.39)
$tradingvol_t$	0.0003	0.00004
	(0.71)	(0.21)
$regulated_t$	0.4840	-0.7491***
	(1.10)	(-2.81)
constant	-2.1533***	0.4977
	(-3.90)	(1.54)
No. of obs.	1,548	1,547
Adj. R^2	0.6174	0.5422

Notes: Table 7 shows the results of the moderating effect of business risk (*stdearnings*) on the association between analyst coverage and media-covered ESG incidents. Column (1) (Column (2)) shows the result of the baseline regression run based on the subsample composed of firms with low (high) business risk. The sample period for the independent variables in the regressions ranges from 2007 to 2015. Year and industry dummies are included in the regressions but 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 level (two-tailed), respectively.

Table 8: Multivariate test of the hypothesis H1b

Variables	Dependent variable = $lnanacov_{t+1}$	
	(1) Low information opacity (*opacity*)	(2) High information opacity (*opacity*)
$avg\_rri\_std_t$	-0.0065	-0.0133**
	(-1.18)	(-2.46)
$size_t$	0.4395***	0.4470***
	(9.47)	(10.17)
$retvol_t$	6.7187	25.2526***
	(1.41)	(6.98)
$stdearnings_t$	0.0223*	0.0350***
	(1.79)	(2.99)
$price_t$	-0.0028***	-0.0012**
	(-2.99)	(-2.11)
$qtrret_t$	-0.0291	-0.2990***
	(-0.44)	(-4.39)
roa_t	-0.3074	0.0675
	(-0.61)	(0.28)
$finconstraint_t$	-0.00004	-0.0001
	(-1.13)	(-1.63)
$r\&d_t$	0.0404	-0.4440
	(0.35)	(-1.47)
$intangible_t$	-1.2781***	0.6036
	(-3.65)	(0.86)
btm_t	-0.0566	-0.1009
	(-0.93)	(-1.08)
$insti_t$	0.1264***	0.1344***
	(4.72)	(6.65)
$tradingvol_t$	-0.0004	-0.0004**
	(-1.32)	(-2.28)
$regulated_t$	-2.5565***	0.3695
	(-4.36)	(0.69)
constant	0.1829	-1.6903***
	(0.42)	(-2.72)
No. of obs.	1,339	1,756
Adj. R^2	0.6565	0.6672

Notes: This table shows the results of the moderating effect of information opacity (*opacity*) on the association between analyst coverage and media-covered ESG incidents. Column (1) (Column (2)) shows the result of the baseline regression run based on the subsample comprising firms with low (high) information opacity. The sample period for the independent variables in the regressions ranges from 2007 to 2015. Year and industry dummies are included in the regressions but 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 level (two-tailed), respectively.

Table 9: Multivariate test of the hypothesis H1c

Variables	Dependent variables = *lnanacov*$_{t+1}$			
	(1) Low product market competition (*substitution*)	(2) High product market competition (*substitution*)	(3) Low product market competition (*mktsize*)	(4) High product market competition (*mktsize*)
$avg\_rri\_std_t$	-0.0083*	-0.0160***	-0.0058	-0.0147***
	(-1.75)	(-2.86)	(-0.89)	(-3.05)
$size_t$	0.4455***	0.4216***	0.4249***	0.4460***
	(9.74)	(9.94)	(8.86)	(10.93)
$retvol_t$	12.2887***	20.6416***	14.2807***	18.1933***
	(2.71)	(5.31)	(3.24)	(4.50)
$stdearnings_t$	0.0444**	0.0152	0.0286*	0.0366***
	(3.02)	(1.34)	(1.97)	(2.82)
$price_t$	-0.0021**	-0.0016**	-0.0012**	-0.0024**
	(-2.44)	(-2.32)	(-2.14)	(-2.50)
$qtrre_t t$	-0.1929**	-0.1916***	-0.1212*	-0.2601***
	(-2.41)	(-3.10)	(-1.91)	(-3.47)
roa_t	0.1847	-0.3487	0.1796	-0.2831
	(0.48)	(-1.33)	(0.47)	(-0.96)
$finconstraint_t$	-2.70e-07	-0.0001***	-0.00003	-0.0001*
	(-0.01)	(-2.61)	(-0.64)	(-1.94)
$r\&d_t$	-0.2731	-0.0589	-0.0519	-0.1591
	(-0.80)	(-0.58)	(-0.44)	(-0.63)
$intangible_t$	-0.8853	-0.4682	-0.2034	-1.0951*
	(-1.61)	(-1.30)	(-0.56)	(-1.91)
btm_t	0.0070	-0.1947**	0.0191	-0.1595*
	(0.13)	(-2.28)	(0.28)	(-2.00)
$insti_t$	0.1426***	0.1118***	0.1114***	0.1410***
	(5.60)	(4.81)	(4.34)	(6.02)
$tradingvol_t$	-0.0004	-0.0003*	-0.0002	-0.0005**
	(-1.50)	(-1.75)	(-0.76)	(-2.29)
$regulated_t$	-0.5372*	0.4310	0.2512	-0.9343***
	(-1.85)	(0.72)	(0.42)	(-7.39)
constant	-0.8992**	-1.2916**	-1.3374**	0.1756
	(-2.19)	(-2.14)	(-2.05)	(0.52)
No. of obs.	1,525	1,570	1,535	1,560
Adj. R^2	0.6415	0.6532	0.6296	0.6672

Notes: Table 9 shows the results of the moderating effect of product market competition on the association between analyst coverage and media-covered ESG incidents. Columns (1) and (2) (Columns (3) and (4)) report the results from using *substitution* (*mktsize*) as the proxy for industrial product market competition. Columns (1) and (3) (Columns (2) and (4)) show the results of the baseline regression run based on the subsamples comprising firms with low (high) industrial product market competition. The sample period for the independent variables in the regressions ranges from 2007 to 2015. Year and industry dummies are included in the regressions but 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 level (two-tailed), respectively.

Table 10: Multivariate tests of the relationship between analyst forecast error and media-covered ESG incidents

Panel A: OLS regression results

Variables	Dependent variable = $error_{t+1}$
$avg\_rri\_std_t$	0.0006***
	(3.44)
$size_t$	-0.0052***
	(-3.18)
$price_t$	0.00003***
	(2.61)
$qtrret_t$	-0.0093***
	(-3.44)
$retvol_t$	0.5771***
	(3.51)
$intangible_t$	-0.0024
	(-0.18)
$tradingvol_t$	8.69e-0.6
	(1.28)
$insti_t$	-0.0036***
	(-4.90)
btm_t	0.001
	(0.29)
roa_t	-0.0504***
	(-2.68)
$finconstraint_t$	-3.38e-06**
	(-2.54)
$horizon_t$	0.0097***
	(4.26)
$change\_roa_t$	-0.0261
	(-1.05)
$change\_eps_t$	0.0308*
	(1.77)
$surprise_t$	-0.0006
	(-0.50)
$gexp\_average_t$	0.0035
	(1.45)
$bsize\_average_t$	-0.0006
	(-0.19)
constant	-0.0299
	(-1.27)
No. of obs.	1,945
Adj. R^2	0.2896

Notes: Panel A reports the result of the OLS regression of analyst forecast error on media-covered ESG incidents. The dependent variable is analyst forecast error (namely, *error*). 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 regressions ranges from 2007 to 2015. Year and industry dummies are included in the regressions but 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 9.77, 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 level (two-tailed), respectively.

Panel B: 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	0.0357	0.189			
roa			-0.066	-0.1572	0.0104
tradingvol			0.1143	0.045	0.0051
change_eps			0.0469	0.1077	0.005
btm			0.0922	0.0314	0.0029
qtrret			-0.0191	-0.1341	0.0026
insti			-0.0134	-0.1781	0.0024
gexp_average			0.0311	0.0602	0.0019
intangible			-0.0351	-0.0424	0.0015
surprise			-0.0338	-0.0396	0.0013
finconstraint			-0.0065	-0.0757	0.0005
change_roa			-0.0121	-0.0381	0.0005
bsize_average			0.0122	-0.0048	-0.0001
price			-0.0708	0.0599	-0.0042
retvol			-0.0619	0.1576	-0.0098
size			0.1352	-0.0988	-0.0134
horizon			-0.1428	0.0967	-0.0138

Notes: Panel B represents the impact threshold for a confounding variable (ITCV) for the regression results presented in Table 10 Panel A, where *error* is the dependent variable, and *avg_rri_std* is the key independent variable, for the regression. The calculation is based on a 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 C: Two-stage least square (2SLS) regression results

Variables	(1) First-stage Dependent variable = $avg\_rri\_std_t$	(2) Second-stage Dependent variable = $error_{t+1}$
$avg\_rri\_std_t$		0.0020***
		(3.33)
lyr_esg_t	1.1247***	
	(12.21)	
$lyr\_esg\_industry_t$	-0.4357***	
	(-2.80)	
$size_t$	0.2298**	-0.0061***
	(2.02)	(-3.52)
$price_t$	-0.0010	0.00005***
	(-0.48)	(3.04)
$qtrret_t$	0.0641	-0.0092***
	(0.35)	(-3.45)
$retvol_t$	-2.3264	0.5908***
	(-0.29)	(3.74)
$intangible_t$	0.2103	-0.0020
	(0.10)	(-0.14)
$tradingvol_t$	0.0010	4.21e-06
	(0.99)	(0.66)
$insti_t$	0.0414	-0.0035***
	(0.93)	(-5.02)
btm_t	0.1371	0.0003
	(0.92)	(0.08)
roa_t	-1.3443*	-0.0470***
	(-1.66)	(-2.60)
$finconstraint_t$	-0.0002	-3.32e-06**
	(-1.34)	(-2.58)
$horizon_t$	-0.8295***	0.0113***
	(-3.23)	(4.80)
$change\_roa_t$	-1.8247	-0.0245
	(-1.63)	(-1.01)
$change\_eps_t$	1.5738***	0.0287*
	(3.05)	(1.70)
$surprise_t$	-0.0548	-0.0005
	(-0.98)	(-0.43)
$gexp\_average_t$	0.0057	-0.0007
	(0.04)	(-0.22)
$bsize\_average_t$	0.1574	0.0031
	(0.96)	(1.31)
constant	1.7375	-0.0345
	(0.94)	(-1.52)
No. of obs.	1,945	1,945
Adj. R^2	0.3621	0.3014

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 *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 the regressions but 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 level (two-tailed), respectively.

Table 11: Multivariate tests of the relation of analyst forecast optimism and forecast pessimism with media-covered ESG incidents

Variables	(1) Dependent variable = $optimism_{t+1}$	(2) Dependent variable = $pessimism_{t+1}$
$avg\_rri\_std_t$	0.0002**	0.0002**
	1.97)	(2.54)
$size_t$	-0.0024***	-0.0006
	(-3.01)	(-1.24)
$price_t$	0.00002**	-2.70e-06
	(2.32)	(-0.64)
$qtrret_t$	-0.0045***	-0.0011
	(-3.32)	(-1.15)
$retvol_t$	0.1625**	0.1932***
	(2.10)	(3.91)
$intangible_t$	-0.0042	0.00057
	(-0.67)	(0.12)
$tradingvol_t$	3.93e-06*	-9.35e-08
	(1.77)	(-0.05)
$insti_t$	-0.0013***	-0.0008***
	(-3.74)	(-3.43)
btm_t	-0.0014	0.0021**
	(-0.91)	(2.14)
roa_t	-0.0169*	-0.0096*
	(-1.74)	(-1.93)
$finconstraint_t$	-1.21e-06*	-6.66e-07
	(-1.93)	(-1.53)
$horizon_t$	0.0037***	0.0017**
	(3.23)	(2.24)
$change\_roa_t$	-0.0017	-0.0042
	(-0.12)	(-0.59)
$change\_eps_t$	-0.0008	0.0076*
	(-0.08)	(1.75)
$surprise_t$	-0.0017***	0.0009**
	(-2.79)	(2.39)
$gexp\_average_t$	0.0023*	0.0002
	(1.81)	(0.26)
$bsize\_average_t$	-0.0018	0.0008
	(-1.04)	(1.12)
constant	-0.0016	-0.0083
	(-0.16)	(-1.27)
No. of obs.	1,945	1,945
Adj. R^2	0.2193	0.1965

Notes: Table 11 reports the result of the OLS regression of analyst forecast optimism (forecast pessimism) on media-covered ESG incidents. For Column (1) (Column (2)), the dependent variable is analyst forecast optimism (forecast pessimism) (namely, *optimism* (*pessimism*)). 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 regressions ranges from 2007 to 2015. Year and industry dummies are included in the regressions but 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 level (two-tailed), respectively.

Table 12: Multivariate tests of the relationship between analyst forecast dispersion and media-covered ESG incidents

Panel A: OLS regression results

Variables	Dependent variable = $dispersion_{t+1}$
$avg\_rri\_std_t$	0.0006***
	(2.67)
$size_t$	-0.0009
	(-0.53)
$price_t$	0.00004**
	(2.09)
$qtrret_t$	-0.0151***
	(-4.43)
$retvol_t$	1.0564***
	(5.85)
$intangible_t$	-0.0112
	(-0.85)
$tradingvol_t$	-3.18e-06
	(-0.39)
$insti_t$	-0.0046***
	(-4.38)
btm_t	0.0067
	(1.54)
roa_t	-0.0797***
	(-2.99)
$finconstraint_t$	-2.26e-06
	(-1.47)
$horizon_t$	0.0126***
	(4.14)
$change\_roa_t$	0.0200
	(0.49)
$change\_eps_t$	-0.0025
	(-0.11)
$surprise\_prioreps_t$	0.0035
	(0.74)
$gexp\_avg_t$	0.0051*
	(1.81)
$bsize\_avg_t$	-0.0028
	(-0.82)
constant	-0.0597**
	(-2.30)
No. of obs.	1,978
Adj. R^2	0.3620

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 regressions ranges from 2007 to 2015. Year and industry dummies are included in the regressions but 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 9.78, 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 level (two-tailed), respectively.

Panel B: 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	0.0169	0.130			
roa			-0.0751	-0.211	0.0158
btm			0.0957	0.0998	0.0096
qtrret			-0.0216	-0.1718	0.0037
insti			-0.0086	-0.1831	0.0016
intangible			-0.0211	-0.0663	0.0014
gexp_average			0.0287	0.0383	0.0011
size			0.1359	0.0066	0.0009
finconstraint			0.0019	-0.0322	-0.0001
change_roa			-0.01	0.0396	-0.0004
change_eps			0.0469	-0.0108	-0.0005
surprise_prioreps			-0.0185	0.0246	-0.0005
bsize_average			0.0114	-0.051	-0.0006
tradingvol			0.1124	-0.0091	-0.001
price			-0.0641	0.0519	-0.0033
retvol			-0.0593	0.2290	-0.0136
horizon			-0.1478	0.0941	-0.0139

Notes: Panel B represents the impact threshold for a confounding variable (ITCV) on the regression results presented in Table 12 Panel A, where *dispersion* is the dependent variable, and *avg_rri_std* is the key independent variable. The calculation is based on a 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 C: Two-stage least square (2SLS) regression results

Variables	(1) First-stage Dependent variable = *avg_rri_std*$_t$	(2) Second-stage Dependent variable = *dispersion*$_{t+1}$
avg_rri_std$_t$		0.0016**
		(2.06)
lyr_esg$_t$	1.1216***	
	(12.09)	
lyr_esg_industry$_t$	-0.4437***	
	(-2.74)	
size$_t$	0.2530**	-0.0016
	(2.19)	(-0.84)
price$_t$	-0.0009	0.00004**
	(-0.45)	(2.34)
qtrret$_t$	0.0595	-0.0150***
	(0.34)	(-4.49)
retvol$_t$	-1.4660	1.0644***
	(-0.18)	(6.08)
intangible$_t$	2.1617	-0.0127
	(0.97)	(-0.95)
tradingvol$_t$	0.0010	-6.27e-06
	(1.05)	(-0.79)
insti$_t$	0.0431	-0.0046***
	(0.96)	(-4.49)
btm$_t$	0.1554	0.0062
	(1.01)	(1.42)
roa$_t$	-1.5159*	-0.0771***
	(-1.95)	(-2.98)
finconstraint$_t$	-0.0001	-2.24e-06
	(-1.11)	(-1.50)
horizon$_t$	-0.8512***	0.0138***
	(-3.34)	(4.27)
change_roa$_t$	-1.8363*	0.0210
	(-1.88)	(0.53)
change_eps$_t$	1.5016***	-0.0039
	(3.16)	(-0.17)
surprise_prioreps$_t$	-0.1323	0.0036
	(-0.85)	(0.77)
gexp_average$_t$	0.1639	0.0048*
	(0.99)	(1.75)
bsize_average$_t$	-0.0033	-0.0028
	(-0.02)	(-0.84)
constant	1.4991	-0.0625**
	(0.82)	(-2.47)
No. of obs.	1,978	1,978
Adj. R^2	0.3615	0.3563

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 *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 the regressions but 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 level (two-tailed), respectively.