ESG news, future cash flows, and firm value*

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Abstract

We investigate the expected consequences of negative ESG news on firms' future profits. After learning about negative ESG news, analysts significantly downgrade their forecasts at short and longer horizons. Negative ESG news affect forecasts more strongly at longer horizons than other types of negative corporate news. The negative revisions of earnings forecasts following negative ESG news reflect expectations of lower future sales (rather than higher future costs). Quantitatively, forecast revisions can explain most of the negative impacts of ESG news on firm value. Analysts are correct to revise forecasts downward following negative ESG news and ESG sensitive analysts tend to provide more accurate forecasts.

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1 Introduction

The use of environmental, social, and governance (ESG) information has become a frequent theme in asset management. For instance, The Forum for Sustainable and Responsible Investment (US SIF) estimates that between 1995 and 2020 the amount of US-domiciled sustainable investment assets has increased 25-fold to about $16.6 trillion at the beginning of 2020 (see SIF (2020)). Launched in 2006, the UN-supported Principles for Responsible Investment (PRI) initiative counted over 4,000 signatories globally representing collective AUM of close to US $121 trillion at the end of 2021. Signatories of the PRI commit to "incorporate ESG issues into investment analysis and decision-making processes" and Gibson et al. (2022) find that more than half of the stock of global institutionally owned public equity is now held by PRI signatories.

While ESG has received increasing attention not only in practitioner circles but also among academics (see, for instance, Gillan et al. (2021) for a survey), the extent to which ESG information matters for firm value is still widely debated. In addition, the channels–if any–through which ESG information affects the value of firms are poorly understood.

The first channel through which ESG related information might affect firm value is related to the impact of divestment on firms' cost of capital. If firms with poor ESG reputations are shunned by a sufficiently large pool of investors, their cost of capital should be higher; hence, firm values should be lower. Such a *discount rate* channel has been modeled by Heinkel et al. (2001) and, more recently, Pastor et al.

(2019) and has been empirically tested by Hong and Kacperczyk (2009), Luo and Balvers (2017), Bolton and Kacperczyk (2021). Second, ESG could potentially affect stock market values if ESG metrics are predictors of the future earnings of the firm. For instance, if a firm is subject to negative ESG news, such as the revelation of unexpectedly high levels of pollution, shareholders might downward revise earnings forecasts due to binding regulatory constraints, potential liabilities, or negative reactions from customers. Such real implications of ESG information for firm earnings might be either short-term (e.g., through a fine or the settlement of a lawsuit) or, potentially, longer term, for instance, because customers or employees turn their back on firms with poor ESG profiles or because the firm's production technology cannot be changed rapidly. If some investors are unaware of the importance of ESG information for future earnings, such information might predict both contemporaneous and future stock returns. This *cash flow* channel is modeled in Pedersen et al. (2019), and evidence of investor underreaction is provided, for instance, in Edmans (2011) or Gloßner (2021).

The main goal of our study is to investigate the *cash flow* channel: to address this question, we consider earnings forecasts made by security analysts and ask how forecasted earnings change following negative ESG news? Does negative ESG news affect forecasts at all horizons equally, or are analyst reactions, for instance, weaker at short horizons (one quarter), and stronger at longer horizons (three years)? Of interest is also the mechanism through which analysts believe negative ESG news to affect earnings: specifically, are changes in earnings forecasts due to changes in expected sales or expected margins? We also ask if analysts should react to negative

ESG news, or whether forecasts would be more accurate when ignoring such news events.

To investigate these questions, we combine a global sample of analyst forecasts of earnings, sales, and margins over various horizons with negative ESG news data. Analyst forecast data serve as a proxy for expectations about future firm fundamentals. The negative ESG news data capture salient point-in-time shocks to analysts' beliefs about the ESG characteristics of firms. Our approach is to explore whether and how analysts change their earnings forecasts as a result of learning about these negative ESG incidents. Using ESG news data rather than ESG ratings (or scores) allows us to avoid the well-documented inconsistency of ESG ratings. For instance, Berg et al. (2022) and Gibson-Brandon et al. (2021) document disagreement in the ESG ratings issued by different data providers. In addition, Berg et al. (2021) document backfilling issues in the Refinitiv ESG data, a widely used ESG dataset. Besides these methodological issues, another concern with using ESG ratings is that these ratings are typically slow-moving, and it is difficult to isolate why and when ESG ratings change. In contrast, focusing on news-related ESG data allows us to identify precise shocks to the ESG information set of financial analysts.

Our analysis delivers several novel stylized facts. Exploiting the rich term structure of earnings forecasts, we provide evidence that negative ESG news shifts earnings forecasts over both short *and* longer horizons. The reaction is stronger when firms are subject to multiple negative ESG news incidents and when the news is related to social issues. We also find that the implications of negative ESG news for future earnings are not redundant with those of other proxies for firm quality (e.g., profitability) available at the time the news becomes available, suggesting that ESG news is not captured by existing accounting information. Moreover, when contrasting earnings forecast revisions following negative ESG incidents with analyst reactions to other types of negative events (e.g., executive changes, reorganizations), we find that negative ESG incidents have a longer-term impact on earnings forecasts than other events. Specifically, we establish that the analyst reaction to negative ESG news is approximately constant across horizons, whereas other types of negative events result in a more pronounced negative reaction in the short-term. Another way of interpreting this finding is that while negative ESG news events appear to result in a permanent shift in EPS earnings forecasts (i.e., roughly constant over horizons), analyst reactions with respect to other types of negative corporate news events appear more transitory (i.e., stronger at short (1-year), and weaker for longer horizons (3-years)). We also provide evidence of considerable heterogeneity in our main result by geographic region, industry, and firm size. For instance, we find that our ESG forecast revision effect is stronger for smaller firms and in B-to-C sectors (where advertising expenses are higher).

After establishing these basic and novel facts, we decompose earnings forecast revisions into a component coming from revisions of expected sales and a component coming from revisions of expected sales. Analysts could expect customers to avoid buying from firms that are subject to negative ESG incidents. Another possibility is that firms cannot easily adjust their production technology to undo the negative ESG implications highlighted by the occurrence of the negative events. Future earnings could then decrease (even if sales are stable) mainly through ESG incidents leading to increased costs. Our analysis suggests that the ESG induced changes in analysts' earnings expectations are primarily driven by the anticipation of lower sales rather than expectations of higher future costs.

As explained above, ESG might affect firm value through a cash flow or a discount rate channel. While the main objective of our paper is to shed light on the importance of the cash flow channel, we also evaluate the relative importance of both channels in driving stock market values following negative ESG events. Using a simple dividend discount approach, we decompose negative ESG news induced changes in firm value in a component coming from changes in cash flow expectations and a component resulting from changes in discount rates. Our analysis shows that changes in earnings forecasts can account for most of the negative response of firm valuations following ESG incidents. The implied change in the discount rate is not statistically significantly different from zero. While we cannot fully rule out that the discount rate channel is also at play, we believe that the majority of changes in firm values result from changes in expected cash flows. Our finding of no changes in implied discount rates is in line with the conclusions of Berk and van Binsbergen (2022), who show that ESG divestment has no detectable effect on the cost of capital of firms. Using a slightly different setting, Lindsey et al. (2021) obtain a similar conclusion, namely that ESG scores do not convey novel information about systematic risk beyond what is already known from other firm characteristics (e.g., quality, volatility, etc.). Our findings are also consistent with recent papers showing that a large fraction of medium-term stock price movements can be attributed to changes in earnings expectations (Engelberg et al. (2018); Loechster and Tetlock

(2020); DeLaO and Myers (2020)) rather than changes in discount rates.

In the final part of the paper, we examine the extent to which ESG sensitive analysts are better forecasters. We first ask whether analysts are correct in downward adjusting EPS and sales forecasts following negative ESG news. We find that, on average, downward revisions of earnings forecasts after negative ESG incidents are warranted and associated with lower forecast errors (compared to a counterfactual of no-revision). Secondly, we exploit the rich IBES analyst-by-analyst forecast data and estimate an individual analyst-level ESG-sensitivity. Using the analyst-level ESG sensitivity as an explanatory variable, we find that more ESG sensitive analysts issue more precise forecasts, but the difference is statistically significant only in Europe. Overall, however, these findings suggest that the recognition of ESG concerns is rational rather than a "fad".

Literature Review. The question of whether and how ESG issues contribute to financial performance is still widely debated, both among practitioners and academics. For instance, Hong and Kacperczyk (2009), Bolton and Kacperczyk (2021), and Pástor et al. (2022) present evidence of out-performance by stocks with low ESG performance, while other papers present evidence of out-performance of high ESG stocks(e.g., Kempf and Osthoff (2007), Edmans (2011)). Focusing on measures of valuation, some researchers have documented a positive correlation between ESG scores and firm value (e.g., Ferrell et al. (2016)). Other papers in the literature have attempted to identify specific mechanisms through which ESG policies might affect cash flows and valuation. For instance, Servaes and Tamayo (2013) stress that a firm's ESG policies can affect consumer behavior, thereby enhancing cash flows and firm value for consumer facing companies. In a similar spirit, Krueger et al. (2021) focus on another key stakeholder (i.e., workers) and provide evidence that firms with better ESG policies pay lower wages, highlighting that ESG policies can generate higher value for shareholders through a reduction in labor costs.

Another stream of the literature has focused on the cost of capital by examining the effect of ESG policies on measures of (systematic) risk. Dunn et al. (2018) and Albuquerque et al. (2019), for instance, provide evidence that better ESG policies are associated with lower systematic risk. More recently, however, Lindsey et al. (2021) construct a rich dataset using ESG scores from seven major ESG data providers and combine these ESG scores with a large set of other stock characteristics (see Jensen et al. (2021)). Contrary to some prior studies, they conclude that when controlling for a substantial amount of the conditioning information investors have at their disposal, ESG measures do not convey novel information about systematic risk.

Our paper is also related to a series of recent papers that use RepRisk data. For instance, Akey et al. (2021) show that reputation-related Reprisk incidents negatively affect firm value. Related to our work are also two other papers that use RepRisk data but with different focuses. Gantchev et al. (2022) document divesting by responsible investors following negative environmental and social (E&S) incidents. They show that firms owned by more responsible shareholders experience larger temporary declines in valuations and react by subsequently improving their ESG performance. Also using RepRisk, Gloßner (2021) finds that negative ESG information shocks predict negative future stock returns, suggesting underreaction to such information in the stock markets.

2 Data

2.1 RepRisk and other ESG scores

Our main ESG data come from RepRisk. RepRisk produces daily indicators for negative ESG-related incidents at the firm level. It does so through a daily analysis of a large set of documents in 20 languages obtained from public sources. The data go back to January 2007, with daily granularity. RepRisk classifies ESG incidents according to 28 distinct issues. Environmental issues include news about climate change, pollution, waste issues, etc. Social issues include child labor, human rights abuses, etc. Governance issues include executive compensation issues, corruption, etc.[1] One incident can be associated with multiple issues and therefore can belong to two or more E/S/G categories. Table IA2 shows the distribution of incident types. Approximately half of the incidents are associated with two or more E/S/G categories. Figure 1 shows the average number of monthly incidents by year. The number of ESG incidents recorded by RepRisk has increased with time. Events related to social issues are the most frequent in the RepRisk data. At the beginning of the sample period, there are more environmental than governance incidents, while at the end of the sample period, there are more governance incidents. In addition, RepRisk categorizes ESG incidents based on their novelty, reach, and severity. The novelty, reach, and severity of incidents are measured on a scale from one to three, where three represent the most novel, most influential, or most severe incidents.

$\boxed{\text{Figure 1 about here.}}$

[1] Table IA1 shows the full list of issues.

To explore the relation between RepRisk incidents and the ESG scores used in the existing ESG literature, we also use ESG scores from Asset4 (now Refinitiv), Sustainalytics (now Morningstar) and MSCI. Asset4 and Sustainalytics provide monthly ESG scores, while MSCI updates its ESG scores at least once per year. To be consistent, we forward fill the MSCI ESG scores to the monthly level. We scale all the scores to 0-100 to make them comparable. We match RepRisk with these datasets through international securities identification numbers (ISINs). In Appendix A, we show that a strong and significantly negative relation exists between ESG events and subsequent ESG ratings. The latter finding justifies our use of ESG incidents as negative shocks to the ESG profiles of firms.

2.2 IBES

We collect monthly analyst consensus forecasts of earnings per share (EPS), sales, gross margins, long-term growth (LTG), and price targets (PTGs) from the Institutional Brokers Estimate System (IBES). EPS, sales and gross margin forecasts are issued over 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizons. We use only forecasts up to 3 years because the forecasts for longer horizons are missing for a large subset of the firms. The LTG forecast from IBES represents the expected annual rate of growth in operating earnings over the company's next full business cycle. In general, LTG forecasts refer to a period of between three and five years. The PTGs from IBES represent the projected price level within a specific time horizon forecasted by the analysts. We restrict our sample to PTGs for 12 months.

To match the monthly IBES consensus forecasts to the RepRisk data, we aggregate all the RepRisk ESG incidents that occurred between two summary statistic dates to the monthly level. Specifically, for two consecutive consensus forecast summary statistic dates d_{t-1} and d_t, we consider ESG incidents occurring on dates within $[d_{t-1}, d_t)$ to be the number of ESG incidents in month t, and we create two variables: an indicator variable equal to one if there is at least one incident in month t (*incidents*) and a variable that counts the number of incidents occurring in month t (*num_incidents*). Figure 2 illustrates the timing of the merge. In this example, three incidents are reported during $[d_{t-1}, d_t)$, so in month t, $incidents_t = 1$ and $num\_incidents_t = 3$. No ESG incidents are reported during $[d_t, d_{t+1})$, so $incidents_{t+1} = 0$ and $num\_incidents_{t+1} = 0$.

Figure 2 about here.

2.3 Stock returns, fundamentals and other events

We collect daily US stock returns from the Center for Research in Security Prices (CRSP) and the daily stock returns of international firms and firm fundamentals from Compustat. We merge the CRSP/Compustat data with IBES using the last trading day before the IBES consensus forecast date. For US companies, we match the CRSP/Compustat data with IBES using CUSIP numbers. For international companies, we match the Compustat data with IBES using SEDOLs. We merge the Compustat data with IBES using the last observable financial statement on the consensus forecast date. We consider a financial statement to be observable only after the earnings announcement (or publication) date rather than the fiscal year end date to avoid look-ahead bias. To make firms in the international sample comparable, we convert all currencies to US dollars using daily exchange rates. In some of the tests, we use the advertisement expenditure of firms, which is only available for the US sample but is still missing for a large fraction of the sample. We first construct firm-level advertisement intensity, which is defined as advertisement expenditure scaled by revenue. We then take the median advertisement intensity of each industry (GICS2) as the industry-level advertisement intensity and assign that measure to all the firms in the relevant industry. We merge the CRSP-Compustat-IBES sample with the RepRisk data using ISINs. We require that the firm exists in all the data sources to be included in the final sample.

We complement our matched dataset with event data from the Capital IQ Key Developments database, which provides structured summaries of material news and events for companies worldwide. The events retained in the Capital IQ Key Developments dataset are related to issues such as, for instance, executive changes, M&A rumors, SEC inquiries, and many more. We use event dates and event types and merge the key development data with our main data through ISINs.

2.4 Construction of key variables

Our analysis focuses on changes in forecasts. For EPS forecast $F_t EPS_{t+h}$ made in month t for horizon h, we define the change in the EPS forecasts between months

$t-1$ and t as $\Delta F_t EPS_{t+h} = \frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})}$. We scale the forecast change by the absolute value of the initial forecast to address negative forecasts.[2] Similarly, the change in PTGs is defined as $\Delta PTG_t = \frac{PTG_t - PTG_{t-1}}{PTG_{t-1}}$. We drop negative sales forecasts and negative gross margin forecasts (less than 0.5% of our sample) and define the change in sales forecasts as $\Delta F_t Sales_{t+h} = \frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{F_{t-1} Sales_{t+h}}$ and the change in gross margin forecasts as $\Delta F_t GrossMargin_{t+h} = \frac{F_t GrossMargin_{t+h} - F_{t-1} GrossMargin_{t+h}}{F_{t-1} GrossMargin_{t+h}}$. Since LTG forecasts are already in percentage terms, we define the change in LTG forecasts as $\Delta LTG = LTG_t - LTG_{t-1}$.

In our regressions, we control for observed changes in the key fundamentals of the firms. We first forward fill the annual accounting variables to the monthly level, time stamped based on the publication date of the financial statement. Next, we construct the changes in the return on assets, capital expenditures, and net debt of the firms as $\Delta ROA_t = ROA_t - ROA_{t-1}$, $\Delta(\frac{Capx}{Asset})_t = (\frac{Capx}{Asset})_t - (\frac{Capx}{Asset})_{t-1}$, and $\Delta(\frac{NetDebt}{Asset})_t = (\frac{NetDebt}{Asset})_t - (\frac{NetDebt}{Asset})_{t-1}$, respectively. By construction, the controls in month t are nonzero only if there is a new financial statement published in month t. We winsorize all ratios at 2.5% and 97.5% to remove the impact of outliers.

Our final sample includes 76,541 ESG incdients of 8,054 firms from 45 countries or regions.[3] There are 2,635,412 firm-month-horizon level EPS forecasts, 2,538,492 firm-month-horizon level sales forecasts, 1,271,860 firm-month-horizon level gross

[2]In our sample, 5.5% of earnings forecasts have negative values. Our results are unchanged if we eliminate these observations.

[3]The countries (regions) include the United States, Japan, Korea, Canada, the United Kingdom, India, Taiwan, Germany, Brazil, Australia, France, the Cayman Islands, Switzerland, Malaysia, Norway, Spain, Italy, Indonesia, South Africa, Sweden, Mexico, China, Bermuda, the Netherlands, Finland, Hong Kong, Denmark, Singapore, the Philippines, Turkey, Poland, Belgium, Russia, Austria, Israel, New Zealand, Chile, Portugal, Pakistan, Nigeria, Thailand, Greece, Ireland, Luxembourg, and Argentina. Table IA3 shows how the sample is distributed across countries.

margin forecasts, 604,370 firm-month level PTG forecasts, and 226,939 firm-month level LTG forecasts. In the full sample, 7.43% of observations have exactly one ESG incident, and 4.73% of observations have at least two ESG incidents. Table 1 reports the summary statistics of the main variables used in the analysis.

Table 1 about here.

3 Baseline: Reaction to ESG incidents

To examine how analysts react to ESG incidents, we conduct panel regression analysis for different horizons. The objective is to understand first whether analysts believe that ESG incidents affect future cash flows and, second, the term structure of this effect, i.e., whether ESG incidents have only a short-term effect (i.e., at the quarterly or one yearly horizon) on profits or instead reflect issues that will materialize mostly over longer horizons (that is up to three years ahead). For this analysis, we consider the forecasts for different horizons separately. Specifically, we use forecasts for the one-quarter to three-year horizons and estimate the following regression for each horizon h:

$$\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1}EPS_{i,t+h})} = \alpha + \beta\, \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t} \tag{1}$$

The dependent variable is the change in the consensus EPS forecasts between two consecutive months $t-1$ and t, scaled by the absolute value of the consensus EPS forecast in month $t-1$. We also consider analysts' PTGs and calculate the change in the consensus PTG between months $t-1$ and t scaled by the PTG in month $t-1$. The main independent variable in these tests is an indicator variable equal to one if RepRisk reports at least one ESG incident between months $t-6$ and t. We aggregate the ESG incidents in months $[t-6, t]$ to take into account the fact that ESG incidents are serially-correlated[4]. We include firm fixed effects in these regressions, as the number of ESG events varies significantly across firms and is explained by time-invariant firm characteristics. To account for the strong industry effect in ESG events and its time-varying and location-varying nature, we also include month $\times$ industry $\times$ country fixed effects in the regressions. We double cluster the standard errors at the firm and month level to account for possible dependence across firms and months.

Table 2 about here.

Panel A of Table 2 shows that the effect of ESG incidents on earnings forecasts is negative over all horizons, statistically significant for most horizons, and approximately constant across horizons. For example, the monthly change in the earnings forecasts for the one-quarter horizon (-0.158 %) is roughly equal to that for the two- or three-year horizons (-0.143 and -0.150 %, respectively). We conclude that following ESG incidents, there is an almost parallel shift in analysts' EPS forecasts. This

[4] Gloßner (2021) document that firms' past ESG incidents predict more future incidents. We also confirm this in our sample, as shown in Appendix Table IA4. Our results are robust to aggregating the ESG incidents in months $[t-3, t]$, $[t-9, t]$ or $[t-12, t]$. The results of the robustness test are reported in Table IA5.

is confirmed in Column (8), in which the effect of ESG incidents on the forecasted long-term growth (LTG) of EPS is economically and statistically insignificant. The last two columns of the table report the relative change in PTGs and stock returns following ESG incidents. The two effects are significantly negative and of similar magnitudes. Analysts' downward adjustments of price targets (Column 9) are of a similar magnitude as observed price movements following ESG incidents (Column 10).[5]

In Panel B of Table 2, we refine the analysis by considering how the number of incidents in a given six-month period affects EPS forecasts, PTGs and returns. Intuition suggests that analysts' reactions should increase with the number of incidents. In line with this intuition, the reactions are both economically and statistically significantly more pronounced for firms that have had at least two incidents in the last six months compared to firms for which RepRisk reports only one incident. For example, decreases in EPS forecasts vary from approximately 0 to -0.113 % across all forecast horizons for firms with one incident in the past six months, while they vary between -0.125 and -0.302 % for firms with at least two incidents during the same period. Again, firms with the strongest analyst reactions, i.e., those with at least two negative ESG events in the last six months as reported by RepRisk, have changes in the EPS forecasts of analysts that are roughly constant across all horizons.[6]

[5] The results are robust to alternative specifications. For example, adding firm-level time-varying controls does not affect our conclusions. Similarly, replacing firm fixed effects with month $\times$ industry $\times$ country fixed effects and adding firm-level controls leads to very similar conclusions. Our results are also robust to controlling for changes in firm fundamentals. These results are presented in Appendix Tables IA6, IA7, and IA8.

[6] Appendix Table IA10 reports analyst reactions by ESG incident type. The impact of E incidents on forecast changes appears to be less significant than that of incidents concerning S and G matters. S and G incidents have about the same effect. The insignificance of E incidents is likely due to

To explore the term structure of the analysts' reactions to ESG events in greater detail, we now contrast the analysts' reactions to ESG events with their reactions to other negative informational shocks. We estimate the same regression specification as in Equation 1 but replace the ESG incident variable with a variable capturing the occurrence of other types of events, i.e., events recorded in the Capital IQ Key Developments database that have negative price implications. Out of the 153 types of events that Capital IQ retains in its database, we identify 33 types that have a significantly negative impact on firm earnings forecasts over a one-year horizon. Table IA9 reports the detailed estimates of the impact of these negative events across different forecast horizons. To compare the term structure effects of different events, we estimate their impact on earnings forecasts at different horizons as we do in Table 2. We then normalize the estimated impact coefficients by their impact at the one-year horizon and represent them graphically in Figure 3.

Figure 3 about here.

As shown in Figure 3, ESG incidents have an impact that persists more over longer horizons than it does for typical negative corporate news. On average, the impact of an ESG incident on earnings forecasts over the three-year horizon is about 36%

the fact that the E incidents reported by RepRisk are not as serious as incidents in the two other categories. In Appendix Table IA11, we split the treatment group into firms with one incident and those with two or more incidents. In months with more than one E incident, there is a significantly negative effect on analyst forecasts, which implies that analysts react more strongly to series of negative environmental incidents. Appendix Table IA12 reports the results of a regression in which we consider only the incidents for which RepRisk's reach, novelty, and severity measures are equal to or larger than two. The effect of novel incidents is not different from that of other incidents. However, high-reach and high-severity incidents have stronger effects than other incidents. In the rest of the analysis, we do not differentiate across the ESG incident types.

higher (0.150/0.110=1.36, from Table 2) than the impact of an ESG incident on one-year earnings forecasts. By contrast, the impact of other types of events diminishes over longer horizons. For example, for credit rating downgrades, the impact on 3-year earnings forecasts is 45% lower (0.84/1.51=0.55; see Appendix Table IA9) of the impact on 1-year earnings forecasts. A similar term structure appears when we use a regression setting. Specifically, we run the following regression:

$$
\begin{aligned}
\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1}EPS_{i,t+h})} = \alpha + \beta\,\mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \\
+ \eta\,\mathbb{1}\{KD\ Negative\ Events\ in\ [t-6,t]\} \\
+ \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

Table 3 reports the estimation results for the above equation. Columns (1) to (3) report the impacts of negative key development (KD) and ESG incidents on earnings forecasts. The impact of an average negative KD event decreases from 0.48% for 1-year forecasts to 0.41% for 2-year forecasts and 0.28% for 3-year forecasts. These differences are significant, as shown in the pooled regressions in columns (4) and (5). In contrast, the difference in the impact of ESG incidents across horizons is not significant (Columns 4 and 5). The F-tests in columns (4) and (5) show that there is a significant difference between the term structure of ESG incidents and that of average negative KD incidents. We conclude that ESG incidents have a longer-lived impact on earnings forecasts than other types of negative incidents.

Table 3 about here.

4 Economic mechanism: Sales vs. costs

Why do analysts anticipate earnings decreases following the occurrence of negative ESG incidents? There are two possible economic mechanisms at play. First, it could be that analysts expect customers to avoid buying from firms that fail to comply with ESG standards. Negative ESG news could shrink the customer base of the firm, which would translate into lower sales. Second, it could be that firms cannot simply and instantaneously adjust their production technology to "repair" the ESG issues. Future earnings could hence decrease (even if sales are stable) in case ESG incidents lead to increased costs, for example, due to the costs of adjusting to existing or future ESG regulations, or simply because ESG incidents lead to monetary penalties for the firms involved.

To understand through which of these two channels (sales vs. costs) analysts anticipate that ESG incidents affect future earnings, we estimate two sets of regression equations similar to Equation 1, replacing changes in earnings forecasts with changes in sales forecasts ($\frac{\Delta F_t Sales_{i,t+h}}{F_{t-1} Sales_{i,t+h}}$) and in gross margin forecasts ($\frac{\Delta F_t GrossMargin_{i,t+h}}{F_{t-1} GrossMargin_{i,t+h}}$), also issued by security analysts.

Table 4 about here.

Table 4 reports the results of these regressions, which suggest that the anticipated decrease in earnings documented earlier is primarily due to a reduction in sales. The coefficients on the ESG incident dummy variable are consistently negative and statistically significant over most horizons in columns (1)-(7) of Panel A where we use changes in expected sales as the dependent variable. Columns (1)-(7) of Panel B suggest that this effect is more pronounced for firms with multiple incidents, as is the case for the effects on earnings forecasts. The evidence from the gross margin regressions (in columns (8) to (14)) is less clear. Following ESG incidents, analysts tend to revise their margin forecasts downwards—if at all—only for very short (i.e., one quarter) and 1-year horizons but not for other horizons. In addition, the coefficient estimates on the incident dummies are only weakly significant. This divergence between sales and margin forecasts is not caused by a difference in numbers of observations, as confirmed in Appendix Table IA13 using a balanced sample. Overall, these results suggest that analysts expect negative ESG incidents to affect future earnings mostly through reductions in sales.

To compare the impact of ESG incidents and other Key Development incidents on expected sales, in Appendix Table IA14 we report the results of regressions similar to Equation 2, replacing the dependent variable with changes in sales forecasts $\frac{\Delta F_t Sales_{i,t+h}}{F_{t-1} Sales_{i,t+h}}$. The ESG incidents have a longer-term impact on sales forecasts compared to other incidents. This result suggests that the longer-term impact of ESG incidents on EPS forecasts (compared to other incidents) comes from the longer-term impact on sales forecasts.

5 Impact on firm value: Cash flow vs. discount rates

There are two potential reasons why stock values decrease after the occurrence of negative ESG events. The first is downward revisions in expected future earnings.

The second is that the cost of capital might have increased, reflecting a smaller set of available investors (as some investors exclude firms with low ESG performance) or a higher level of perceived systematic risk. In this section, we propose an empirical decomposition of the valuation effects of ESG shocks by disentangling the effects of changes in forecasted profits from the effects of changes in discount rates.

5.1 A first intuitive pass using Gordon's formula

The results in Table 2 suggest that following an ESG incident, EPS forecasts decrease by a similar percentage across all horizons (columns 5-7), leaving long-term growth unchanged (Column 8). Assuming the conditions for Gordon's formula for the valuation of a growing perpetuity hold, we can write:

$$PV_{it} = \frac{b_i F_t EPS_{i,t+1}}{r_{it} - g_i}$$

where PV_{it} is the equity value of firm i at time t, b_i is the payout ratio (assumed to be constant over time within firms), and $F_t EPS_{i,t+1}$ is the time t forecast of the next twelve months' earnings. The theoretical firm-level return induced by an ESG information shock is:

$$\frac{\Delta PV_{it}}{PV_{it}} = \frac{\Delta F_t EPS_{i,t+1}}{F_t EPS_{i,t+1}} - \frac{\Delta r_{it} - \Delta g}{r_{it} - g} \tag{3}$$

In our data, Table 2 suggests that the impact of ESG incidents leaves expected growth unchanged ($\Delta g \simeq 0$), while the similarity of the coefficient in Column (10) of Table 2 to the coefficients in columns (5)-(7) translates to $\frac{\Delta PV_{it}}{PV_{it}} \simeq \frac{\Delta F_t EPS_{i,t+1}}{F_t EPS_{i,t+1}}$. This implies that changes in expected future earnings explain most of the changes in firm equity values induced by a typical ESG incident.

5.2 A discounted dividends approach

We now aim to confirm the result sketched above through a somewhat more sophisticated valuation framework than that of the Gordon formula. We rely on the same simple firm-level discounting approach as in Hommel et al. (2021), in which we use information on the term structure of earnings forecasts. Specifically, for each firm i at date t, we define the present value of its future payout per share as:

$$\begin{aligned}\frac{PV_{it}(r_{it})}{b_i} = \frac{F_t EPS_{i,t+1}}{(1+r_{it})^{\theta_{it}}} + \frac{F_t EPS_{i,t+2}}{(1+r_{it})^{\theta_{it}+1}} + \frac{F_t EPS_{i,t+3}}{(1+r_{it})^{\theta_{it}+2}} \\ + \frac{1}{(1+r_{it})^{\theta_{it}+2}} \frac{(1+g_t) F_t EPS_{i,t+3}}{r_{it} - g_t}\end{aligned}$$

where θ_{it} is the fraction of the year remaining until the fiscal year end for firm i at time t. b_i is the payout ratio of the firm. It is estimated as the rolling industry average common stock payout, computed as the sum of dividends (Compustat item *dvc*) and common stock repurchases (total buybacks *prstkc* minus preferred buybacks *pstkrv*), normalized by net income (when net income is positive; otherwise, we ignore the observation). We winsorize the payout ratio at 0 and 1 and then take the average at the industry level. $F_t EPS_{i,t+h}$ is the term structure of the EPS forecasts at time t, and g_t is the expectation of long-run nominal GDP growth given by macro forecasters. Just like in the previous analysis, we do not use forecasts beyond year 3 because they are often missing. For this analysis, we focus only on the US sample, as the expected growth rates and payout ratios are less readily available in other countries. Then, for every observation (i, t), the discount rate r_{it} is the solution to the implicit equation:

$$PV_{it}(r_{it}) = P_{it} \tag{4}$$

where P_{it} is the stock price of firm i at time t. We keep only the values of this discount rate r_{it} that are between 0 and 30%. Our null hypothesis is that ESG incidents do not affect the discount rates used to compute firm values. To explore this hypothesis, we estimate regression equations similar to Equation 1, replacing changes in EPS forecasts with Δr_{it}, expressed in either absolute or relative terms.

Table 5 about here.

Columns (1) and (2) of Table 5 report the results. In the two columns, the coefficient on ESG incidents is marginal and statistically insignificant. In other words, ESG incidents have no discernible impact on the estimated implied rate of return. This suggests that ESG incidents affect the market value of firms mostly through the cash flow channel.

To confirm this, we use a slightly different approach. For each month t and each firm i, we compute the new firm value using the formula above with updated analyst forecasts and the same discount rate, growth rate, and payout ratio as in month $t-1$. We then calculate the percentage change in value between months $t-1$ and t, $\widehat{\Delta PV_{i,t}}/PV_{i,t-1}$, which is the predicted stock return if ESG shocks affect only expected profitability but not the discount rate. We check how ESG incidents affect this predicted return using the same regression setting as above. In Column (3) of Table 5, the coefficient on the ESG incident indicator variable is significantly negative and similar in magnitude to that of the returns or PTG changes observed in Table 2. So, using the simple valuation formula above, changes in earnings forecasts quantitatively match the changes in observed (using returns) or predicted (using analysts' PTGs) firm values. Columns (4) and (5) of Table 5 confirm that in the US sample, the effect of ESG incidents on observed returns (column 4) and predicted returns (column 5) is comparable to the effect on returns of earnings changes alone estimated using our firm value formula. Taken together, the evidence from Table 5 suggests that a cash-flow (or profitability) channel can account for the magnitude of the valuation changes that follow negative ESG news. We do not find evidence of a significant discount rate channel, but this might be due to lack of statistical power in our decomposition.

6 Heterogeneity

In this section, we ask whether the effects of ESG incidents on forecasts and returns vary across countries, industries, and firms. The objective of this analysis is to better understand what drives the sensitivity of analysts to ESG-related events (e.g., the local industry composition or the local sensitivity to environmental or social issues).

6.1 Variation across geographic regions

First, we analyze the heterogeneity across countries, splitting the sample by geographic region. It is possible that the downward adjustment in sales and earnings forecasts varies across regions, for instance because of geographic differences in consumer preferences. To test this hypothesis, we use firms located in North America (the US and Canada) as the base category and further interact the ESG incident variables with dummies indicating $EU15$, $Asia$, and $Others$, where $EU15$ marks the 15 most developed countries in Europe as defined by the United Nations[7] and $Others$ mostly includes firms in South America, Australia, and Africa. We focus on annual forecast data, as quarterly forecasts are predominantly available for US firms.

Table 6 about here.

Panel A of Table 6 reports the effects of ESG incidents on EPS, PTGs, and returns across regions. Along short horizons (1-2 years), there is no significant difference between forecasts for North American firms and firms located in other regions. However, some differences across regions appear in longer horizon forecasts. The interaction of the ESG incident variables with dummies indicating firms from Asia and the *Other* geographic regions are significant and positive, which implies that the 3-year earnings forecasts for firms in Asia and the *Other* region react less to ESG incidents than in other geographic areas. There is not much difference in terms of the reaction

[7]The 15 most developed countries in Europe are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the United Kingdom. See `https://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf`

in PTGs. In contrast, the average reaction in the cumulative returns in developed Europe is stronger than that in North America (see column (6)). Panel B of Table 6 reports the heterogeneous effects on the sales forecasts of firms by geographic region. Consistent with the results for the earnings forecasts, there is no difference across regions in sales forecasts over short horizons. However, analysts adjust their 3-year sales forecasts due to negative ESG incidents less for Asian firms. From the evidence above, we conclude that downward adjustments in earnings forecasts are largely a global phenomenon with only slight geographic differences. For short-horizon forecasts, analysts react similarly for North American firms and firms in other regions, but there is some mild evidence that analysts react less for Asian than for North American firms over longer forecast horizons.

6.2 Variation across industries

Next, we ask whether the link between ESG-related news and analyst forecast revisions is stronger in some industries. Industries vary significantly in their exposure to ESG events. The average number of incidents per industry appears in Figure 4, which shows, for example, that firms in the energy sector are more likely to have ESG incidents in the average month than firms in the real estate sector. Additionally, our previous results show that ESG performance influences future earnings mostly through reduced customer demand. Customers at different locations in the supply chain may not only have different access to information regarding the ESG practices of the firms from which they buy but may also have different sensitivities to the ESG practices of those firms. Our hypothesis is that end customers are both less informed about and more sensitive to the ESG practices of the firms they buy from, so that the effect of salient news items such as those reported by RepRisk should be more pronounced in B-to-C industries than in B-to-B industries. To examine this possibility, we first calculate the analysts' sensitivity to ESG news at the industry level using the same setting as in Table 2 above. We consider the average sensitivity of one-, two-, and three-year earnings forecasts to RepRisk news across all firms in each industry (as defined by GICS2 codes) as our industry measure of ESG sensitivity.

Figure 4 about here.

Figure 5 plots the analysts' sensitivity to incidents in each industry, from the greatest sensitivity (i.e., the industry with the most negative coefficients in the regressions of analysts' forecast changes on ESG-related events) to the lowest sensitivity. As expected, analysts seem to exhibit higher sensitivity to ESG-related news when firms belong to industries selling to end customers. For example, the three industries to which the analysts are most sensitive are "Household and personal products," "Commercial and professional services," and "Consumer services". In line with our previous findings that PTG revisions by analysts are commensurate with their earnings forecast revisions, the ranking of industries using the sensitivity of PTG revisions to ESG news presented in Figure 6 is very similar to the ranking presented in Figure 5.

Figure 5 about here.

Figure 6 about here.

To confirm this result in a more formal setting, we proxy for the extent to which firms from specific industries sell to end customers using data on advertising expenses, following Servaes and Tamayo (2013). Figure 7 plots the advertising intensity of the various industries (measured as $\frac{Advertisement\ Expense}{Revenue}$) against the industry-level sensitivity of analyst forecasts to news, i.e., the industry-level average of the coefficients obtained in Table 2. Panel A of Figure 7 illustrates the sensitivity of earnings forecasts to ESG-related news, while Panel B illustrates the sensitivity of their PTGs. Both panels show a downward-sloping relation, meaning that industries with larger advertising expenses also tend to exhibit greater sensitivity to ESG news in their analyst forecasts (i.e., they have more negative coefficients in Table 2). In Table 7, we split the industries into two groups, B-to-C and B-to-B, according to whether the firm belongs to an industry that is above or below the median of all industries in terms of its advertising expenditure. We then repeat the baseline analysis of Equation 1, adding to the regression the interaction between a dummy measuring high advertisement intensity and the indicator variable equal to one for firms with ESG events in the past six months. The effect of ESG incidents on EPS forecast revisions is stronger (more negative) for firms in B-to-C industries, particularly over the one- and two-year horizons (Panel A). Panel B of Table 7 suggests that sales forecast revisions after ESG incidents are also stronger for firms in B-to-C industries over almost all horizons.

Figure 7 about here.

Table 7 about here.

6.3 Large vs. small firms

We also analyze whether there is heterogeneity by firm size, which we measure using market capitalization. We split the sample into small and large firms. The incidence of RepRisk ESG news items is highly correlated with firm size. Figure 8 shows the number of incidents by size deciles relative to the smallest decile after taking out the country $\times$ industry $\times$ month fixed effects. Firms in the tenth decile have approximately 2.5 times as many ESG incidents per month as firms in the first decile. Therefore, ESG news could possibly be too rare for any effect on small firms to be detectable. On the other hand, investors closely monitor the ESG performance of large firms and could anticipate ESG-related events before they are known to the wider public. In Table 8, we split the sample of firms by firm size, with large firms being defined at the monthly level as those with above-median market capitalization in the given month. We then repeat the analysis of Table 2 for the two groups of firms. The results show that the effect of ESG events on analyst forecasts materializes only for small firms. The coefficient on the interaction between ESG events and the dummy variable equal to one for large firms roughly compensates the coefficient on the event variable alone. In Panel B of Table 8, we repeat the same analysis for sales forecasts. Again, analysts' downward revaluations of future sales that we document above seem to come mostly from small firms, while the effect is less pronounced for large firms. Overall, these results suggest that the information content of RepRisk events appears to be more relevant for small firms.

Figure 8 about here.

Table 8 about here.

7 Analyst revisions and forecast errors

Analysts downward adjust their earnings and sales forecasts following negative ESG incidents. In this section, we evaluate whether analysts' ESG sensitivities have implications for their forecasting skills. We start by examining whether analysts are correct in downward revising forecasts following the occurrence of negative ESG news events. Specifically we are interested in whether forecast downward adjustments are associated with higher or lower forecast errors. To answer this question, we first construct the measure of forecast error, $FError_tEPS_{i,t+h} = (\frac{F_tEPS_{t+h}-EPS_{i,t+h}}{EPS_{i,t+h}})^2$, where $EPS_{i,t+h}$ is the realized earnings of firm i in month $t+h$. Then we define the change of forecast error for each horizon h, $\Delta FError_tEPS_{i,t+h} = FError_tEPS_{i,t+h} - FError_{t-1}EPS_{i,t+h}$. We also construct the measure of changes in sales forecast errors using the same equations. To test whether analysts' reaction to negative ESG news events lead to lower forecast errors, we run the following regressions for both earnings and sales:

$$
\begin{aligned}
\Delta y_{i,t+h} = \alpha &+ \eta\, \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \times forecast\ revision \\
&+ \beta\, \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \\
&+ \xi forecast\ revision \\
&+ \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}
\end{aligned} \tag{5}
$$

where $\Delta y_{i,t+h}$ is either $\Delta FError_t EPS_{i,t+h}$ or $\Delta FError_t Sales_{i,t+h}$, that is the monthly change in EPS or sales forecast error as defined above. Like in the previous analysis, $\mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\}$ is a dummy variable equal to 1 if RepRisk reports at least one ESG incident between months $t-6$ and t. The variable $forecast\ revision$ measures the monthly EPS or sales forecast revision, defined as $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})}$ or $\frac{\Delta F_t Sales_{i,t+h}}{abs(F_{t-1} Sales_{i,t+h})}$. The coefficient of interest is η, which captures the average change in forecast errors after EPS or sales forecast revisions following ESG incidents.

Results, presented in Table 9, show that analysts are correct in downward adjusting EPS and sales forecasts. Columns (1)-(3) and (4)-(6) show the results for EPS and sales forecasts, respectively. For all the horizons of EPS forecasts and 2-3 year horizons for sales forecasts, the interaction of the ESG incident dummy variable and $forecast\ revision$ is positive and significant, which implies that, conditional on ESG incidents, more negative EPS and sales forecast revision lead to lower forecast errors. The magnitude is also economically meaningful. After ESG incidents, a 1% downward adjustment in EPS (sales) forecast is associated with a 0.4% (2%) standard deviation change in forecast error. Therefore, we conclude that analysts are on average correct in downward adjusting EPS and sales forecasts after ESG incidents.

Last, we explore whether the analysts who react more strongly to ESG incidents are more accurate in their forecasts. We first calculate analyst-level ESG sensitivity based on the simple idea that analysts who are more sensitive to ESG concerns revise their earnings forecasts more when they observe ESG incidents. To do so, we regress for each analyst, forecast changes on the ESG news indicator. Note that the term "ESG sensitivity" does not necessarily imply that we attribute this sensitivity to personal preferences. Analysts could also be more ESG sensitive because they work for a broker that is itself more sensitive to ESG-related issues or because the analyst comes from a geographical area where or is from a generation in which the average person is more ESG-conscious. Finally, higher ESG sensitivity could also reflect a better understanding of how current signals about a firm's ESG practices will affect its profitability in the years to come. In this case, we expect that more skilled analysts should be more sensitive to ESG incidents. To examine this possibility, we run the following regression:

$$precision_{i,j} = \alpha + \beta ESG\ sensitivity_j + \gamma X_{i,j} + \sigma_j + \epsilon_j \tag{6}$$

where $precision_{i,j}$ is the forecast precision of analyst j for firm i, defined as the rank of the forecast error in EPS forecasts among all EPS forecasts for the same firm's same fiscal-year earning (we drop EPS forecasts for which fewer than 3 analysts made forecasts), averaged to the analyst-firm level. Following Bouchaud et al. (2019), we keep only those forecasts that were issued at most 45 days after an announcement of fiscal-year earnings. If an analyst issues multiple forecasts for the same firm and the same fiscal year during this 45-day period, we retain only the first forecast. $ESG\ sensitivity_j$ is the ESG sensitivity of analyst j, defined as the coefficient β^j from the following regression $\frac{\Delta F_t EPS^j}{abs(F_{t-1}EPS^j)} = \alpha + \beta^j \mathbb{1}\{ESG\ incidents\ in\ months\ [t-6,t]\}$, which we estimate for each analyst j. We consider only 1-3 year horizon EPS forecasts when estimating sensitivity. The control variables $X_{i,j}$ include $log(age)_j$, the natural logarithm of the number of years since the first forecast made by analyst i; $log(experience)_{i,j}$, the natural logarithm of the number of years since analyst j began following firm i; $specialty$, the share of forecasts made for firm i out of all forecasts; $log(frequency)_j$, the natural logarithm of the number of forecasts made per year; and $log(coverage)_j$, the natural logarithm of the number of firms followed by analyst j. σ_j is the firm fixed effect, which absorbs firm-level characteristics that are related to forecast precision.

Table 10 presents the results. The first column presents the results of the regression with only firm fixed effects. In Column 2, we also control for the characteristics of the analysts. In these two columns, the link between the precision of the analysts and their sensitivity to ESG-related news is positive, but insignificant. The next columns, however, show a striking difference between the US and developed Europe. While ESG-sensitive analysts are not more precise in forecasting earnings for US firms, they are more precise for firms in developed Europe.[8] This suggests that in the US, analysts' sensitivity is a function of their personal taste or that of their brokers or clients, while in Europe, precision and sensitivity to ESG news are related, perhaps

[8]Note that those analysts who revise more strongly (i.e., exhibit more negative values for ESG sensitivity) also rank higher in their forecast accuracy for a given firm (i.e., exhibit lower values for the forecast precision variable).

because ESG news has a greater impact on the operating performance of European firms.

Table 10 about here.

8 Conclusion

Through the use of a global sample, this paper examines how negative ESG news impacts the revisions of earnings forecasts by analysts. Following the occurrence of negative ESG incidents, we document significant downward revisions of earnings forecasts over both short horizons (one quarter) and longer horizons (three years). These downward revisions are due to negative revisions of future sales forecasts, suggesting that analysts expect consumers to react negatively to deteriorating ESG performance. We also provide evidence that stock prices react negatively to the occurrence of negative ESG news. Interestingly, most of the negative impact on stock prices from these ESG news items is quantitatively explained by changes in earnings forecasts. Analysts are on average correct in making the forecast revision after ESG incidents. Moreover, analysts who are relatively more sensitive to ESG news have similar or better accuracy in their forecasts than peers, suggesting that the integration of ESG concerns is actually rational rather than a "fad".

Overall, our results suggest that avoiding negative ESG incidents is an important risk-management concern for companies, as such incidents have a substantial impact on firms' long-term earnings.

Appendix A: RepRisk vs. other ESG data

In this appendix, we validate that the ESG incidents we use for our analysis are indeed related to ESG issues and are not just general negative news about the firms. In addition, we want to confirm that the ESG news reported by RepRisk is related to the more classic ESG scores and ratings provided by other ESG data providers. These ratings are not directly usable for our purposes because they are updated with low frequency and because the reasons why they change are not always clear. Furthermore, the ESG scores produced by traditional ESG data providers agencies aggregate several criteria, including ESG-related news and other quantitative and qualitative information provided by the firms themselves or by other sources. However, the way in which this information is processed and recombined by rating agencies into ESG scores is not always entirely transparent. Moreover, rating agencies frequently change their rating methodologies (Berg et al., 2021), e.g., following acquisitions of other rating agencies, possibly leading to time inconsistencies in the scores. As a result, the literature has found that scores provided by different rating agencies are sometimes difficult to reconcile (Berg et al., 2022). The advantage of using the "ESG news" provided by RepRisk is that it allows the identification of cleanly defined ESG-related events that are likely to affect a firm's ESG outlook. These news events fall under the E, S, and G categories; they reflect salient events in each of these three categories. As such, they are well suited to our analysis. In this section, we want to confirm that the ESG news reported by RepRisk is related to the more classic ESG ratings provided by other ESG data providers.

To verify that despite the reservations about ESG scores discussed above, there is indeed a link between RepRisk news and changes in ESG ratings, we compare the RepRisk news items with the scores provided by three of the most influential ESG rating agencies, namely, Asset4, MSCI, and Sustainalytics. We regress the ESG scores defined at the monthly level and their logarithms on the logarithm of the number of incidents reported by RepRisk in the current and the preceding months:

$$ESG\,Score_{i,t} = \sum_{s=0}^{12} \beta_s log(num.\ ESG\ incidents_{i,t-s}) + \gamma_i + \delta_{t\times Industry} + \epsilon_{i,t}, \quad (7)$$

where $ESG\,Score_{i,t}$ is the ESG score of firm i in month t or its logarithm, depending on the specification. The variable $log(num.\,ESG\,incidents_{i,t-s})$ is the natural logarithm of the number of incidents that happened in month $t-s$. We include 12 lags to account for the dynamic nature of the scores. We also include firm fixed effects since both the scores and the probability of observing ESG-related events are driven to a large extent by time-invariant firm characteristics. Finally, we include month $\times$ industry (GICS2) fixed effects in these regressions because the number of ESG-related news items is likely to exhibit different time patterns in different industries. Following the same logic, we cluster the standard errors at the month $\times$ industry level.

The results reported in Table 11 show a clear connection between ESG scores and ESG-related news, with negative coefficients over all horizons and for all three scores considered. In all but two cases, the coefficients are also statistically significant at conventional levels. Comparing the results across score providers, we see that the results seem stronger, both economically and statistically, for the Asset4 and MSCI ratings than for the Sustainalytics ratings. The latter finding could suggest that

ESG news-related data play a lesser role in the construction of Sustainalytics scores than in the construction of the scores from the other providers. Overall, the evidence presented in Table 11 is consistent with the view that the ESG incidents we consider in our study are part of the information set used by the providers of ESG scores.

$\boxed{\text{Table 11 about here.}}$

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Figures

Figure 1: Number of RepRisk ESG incidents by year

This figure shows the average number of environmental, social and governance incidents by year. The green, red and blue bars represent environmental, social and governance incidents, respectively.

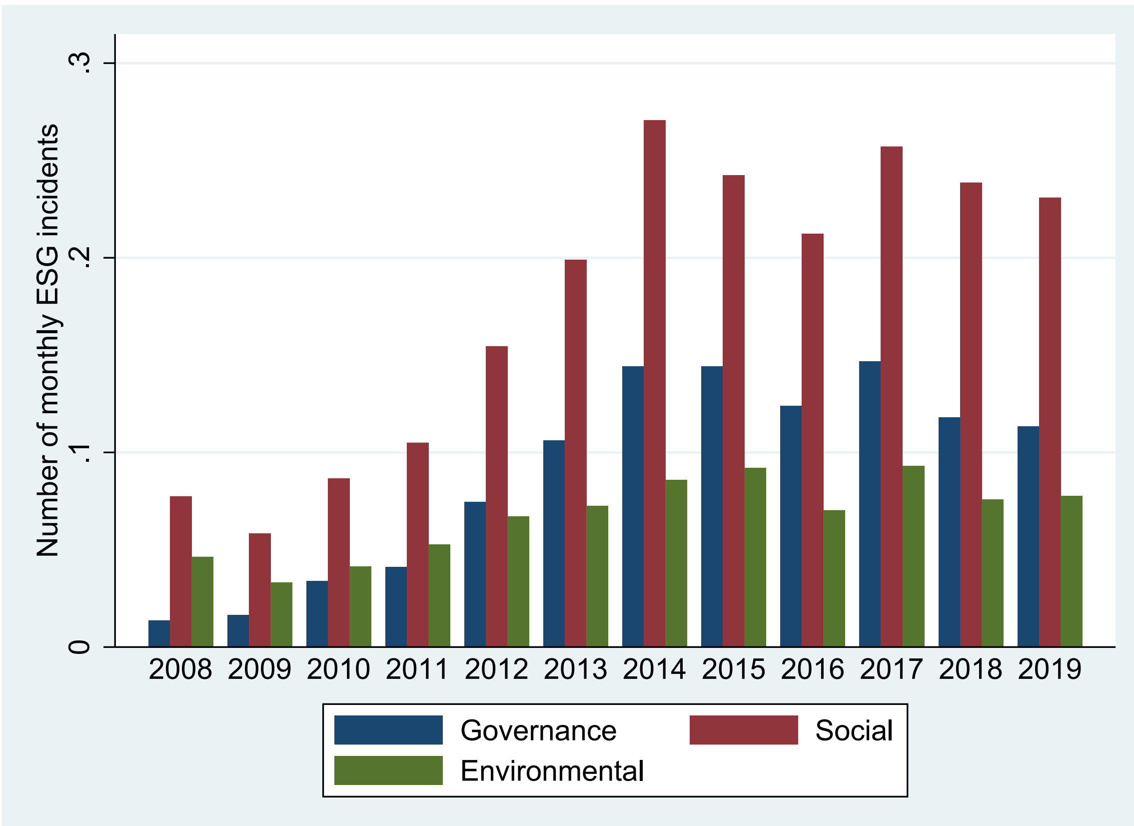


Figure 2: Timing of ESG incidents and analyst forecasts

This figure illustrates the timing of the match between analyst forecasts and RepRisk ESG incidents. d_{t-1}, d_t, and d_{t+1} are three consecutive IBES consensus forecast dates. All ESG incidents reported during $(d_{t-1}, d_t]$ are aggregated and assigned to month t.

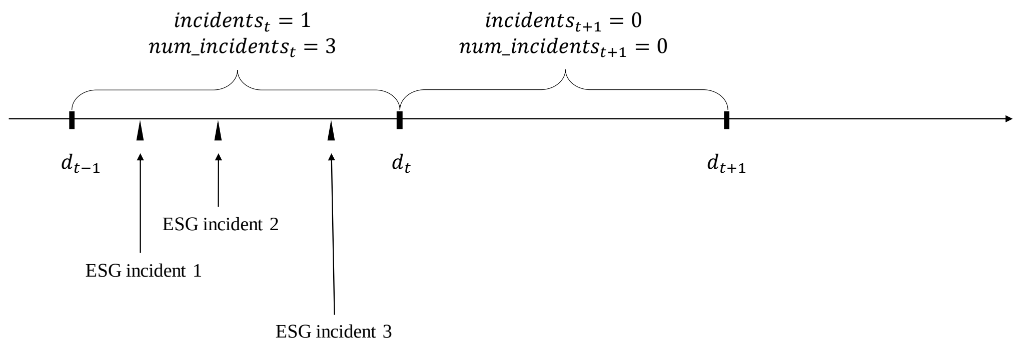


Figure 3: Term structure of the impact on earnings forecasts

This figure reports the term structure of different types of *negative* corporate events. For each event type u and horizon h, we estimate the regression equation $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta_h \mathbb{1}\{type\ u\ incidents\ in\ [t-6,t]\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$, where the dependent variable is the change in EPS forecasts scaled by the lagged absolute EPS forecasts. The independent variable is one if an event of type u happens in months $[t-6,t]$ and 0 otherwise. Detailed estimates for βs are shown in Appendix Table IA9. Then, for each incident type and forecast horizon h, we scale the impact by its impact on the 1-year forecast. On the y-axis is the impact on earnings forecasts scaled by the 1-year forecasts. On the x-axis are the horizons (ranging from one to three years). The blue lines represent the term structure for each type negative events from the Key Developments database. The bold black line represents the average term structure of all negative Key Development events. It can be interpreted as follows: "on average, following a negative corporate event, the percentage revision of 2-year forecasts is only 83% of that of 1-year forecasts". The bold red line represents the term structure of the ESG incidents. It can be read as follows: "on average, following a negative ESG incident, the percentage revision of 2-year forecasts is stronger than that of 1-year forecasts by a factor 1.32".

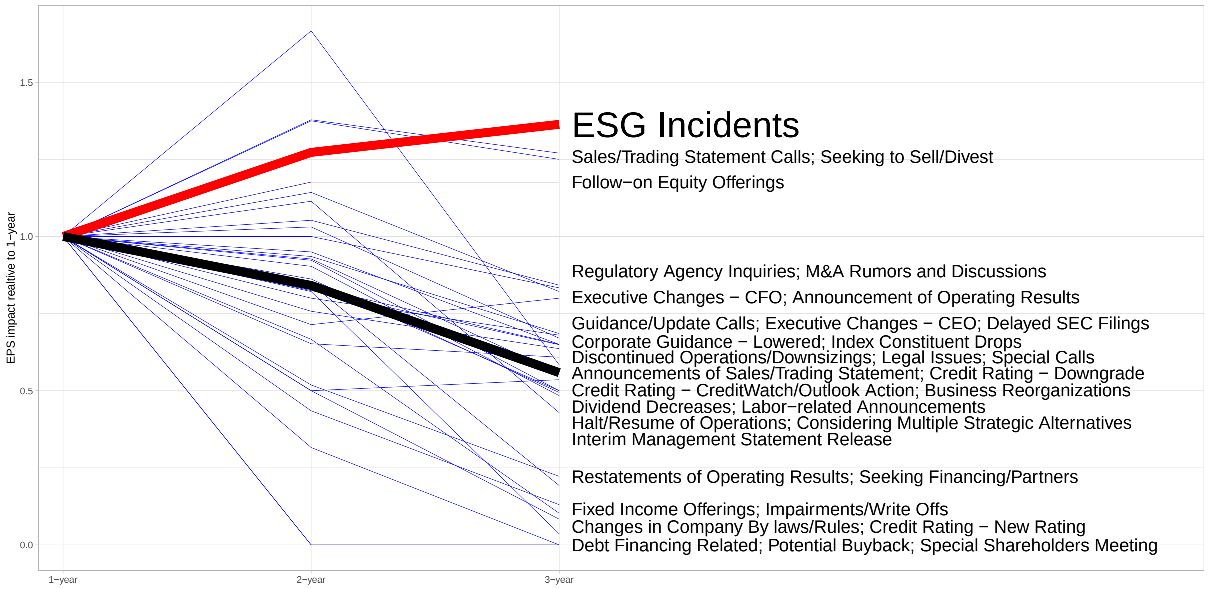


Figure 4: Number of incidents by industry

This figure reports the monthly average number of incidents by industry. Industries are defined according to GICS2 classification.

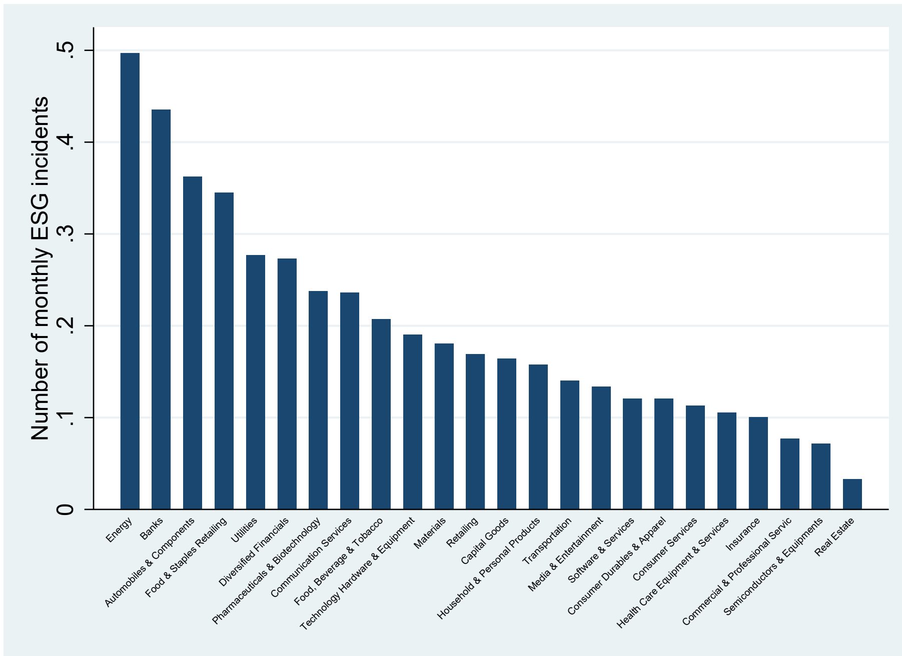


Figure 5: EPS sensitivity by industry

This figure reports the sensitivity of EPS forecasts by industry. The y-axis shows the industries (GICS2), and the x-axis plots the sensitivity of the EPS forecasts to ESG incidents, measured by $\beta_{j,h}$ from the regression equation $\frac{F_t EPS_{i,t+h} - F_{t-1} EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta_j^h \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$. The sensitivity of industry j is measured as the average sensitivity across the 1-3 year horizon forecasts, i.e., $(\beta_j^1 + \beta_j^2 + \beta_j^3)/3$.

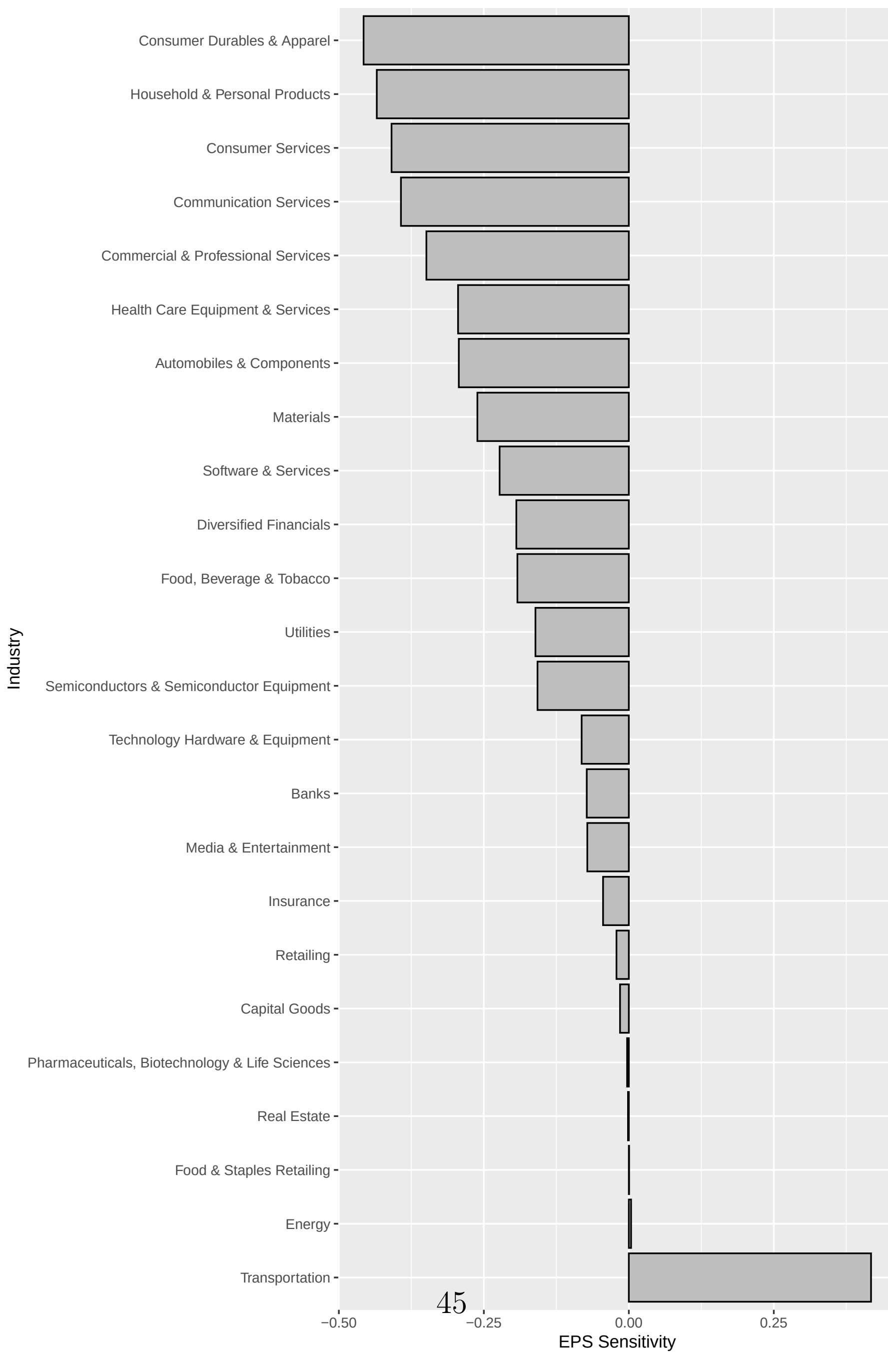


Figure 6: PTG sensitivity by industry

This figure reports the sensitivity of PTGs by industry. The y-axis shows the industries (GICS2). The x-axis shows the sensitivity of PTG forecasts to ESG incidents, measured by β_j from the regression equation $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} = \alpha + \beta_j \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$. The sensitivity of industry j is measured by β_j.

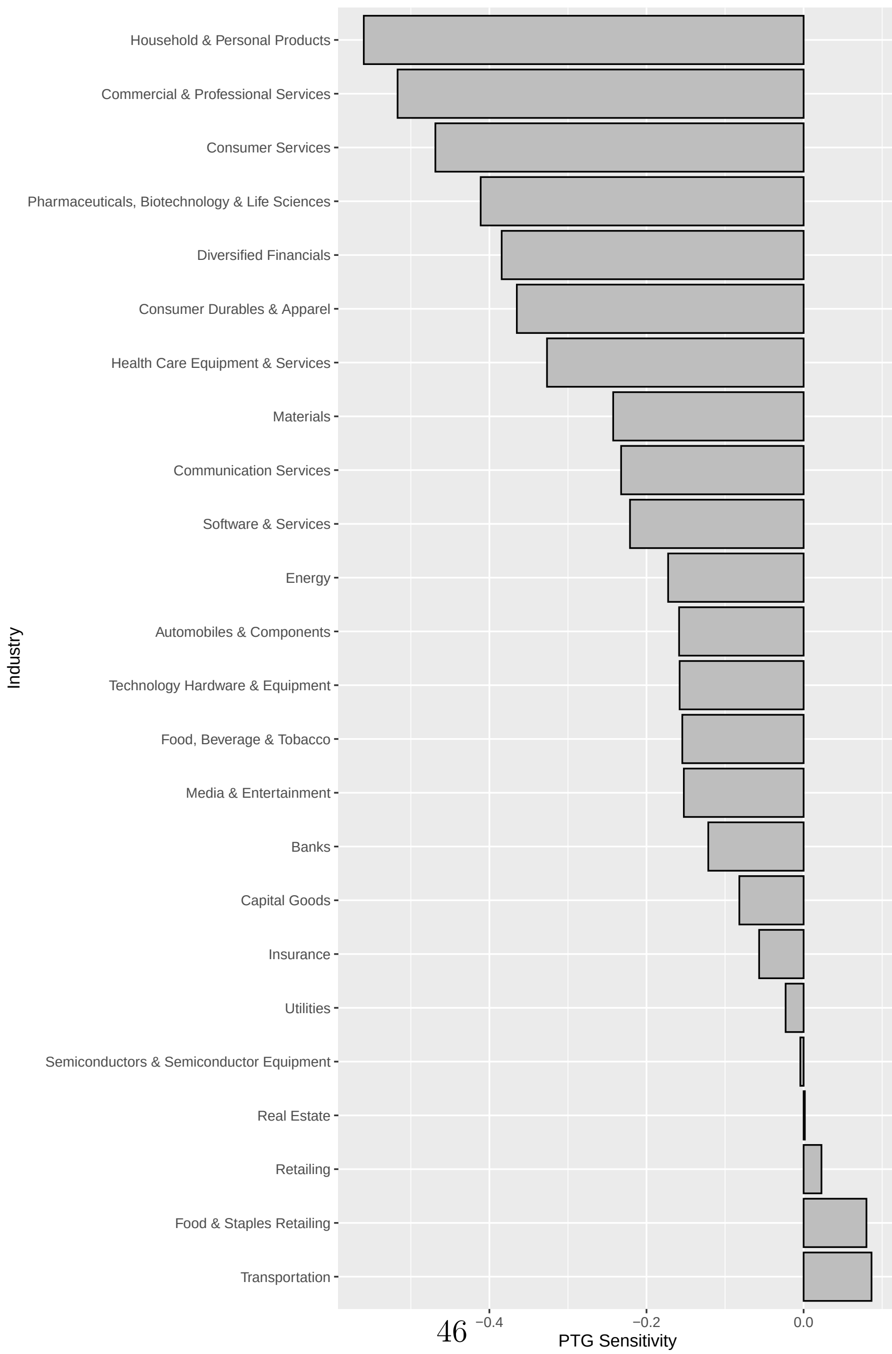
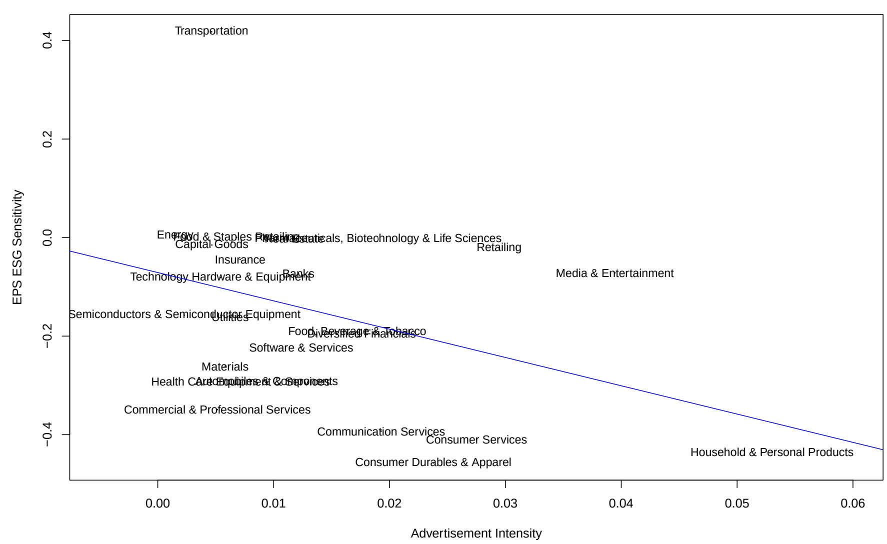


Figure 7: EPS/PTG sensitivity and advertising intensity

This figure reports the relationship between ESG sensitivity and advertising intensity at the industry level. On the y-axis is the advertising intensity, defined as *Advertising expenditure/Sales*. We take the median in an industry as the industry-level advertising intensity. On the x-axis are the ESG sensitivity measures. In subfigure (a), the x-axis plots the sensitivity of EPS forecasts to ESG incidents, measured by $\frac{F_t EPS_{i,t+h} - F_{t-1} EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta_j^h \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$ for each forecast horizon $h = 1, 2, 3$ years. The sensitivity of industry j is measured by $(\beta_j^1 + \beta_j^2 + \beta_j^3)/3$. In subfigure (b), the x-axis plots the sensitivity of PTG forecasts to ESG incidents, measured by β_j from the regression equation $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} = \alpha + \beta_j \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$. The sensitivity of industry j is measured by β_j. The blue lines in the two graphs are the corresponding linear fits.

(a) EPS sensitivity



(b) PTG sensitivity

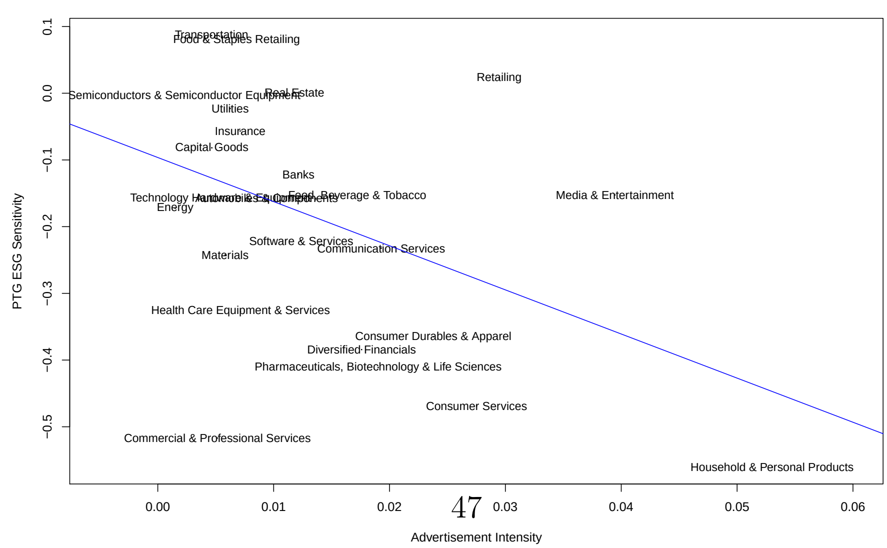
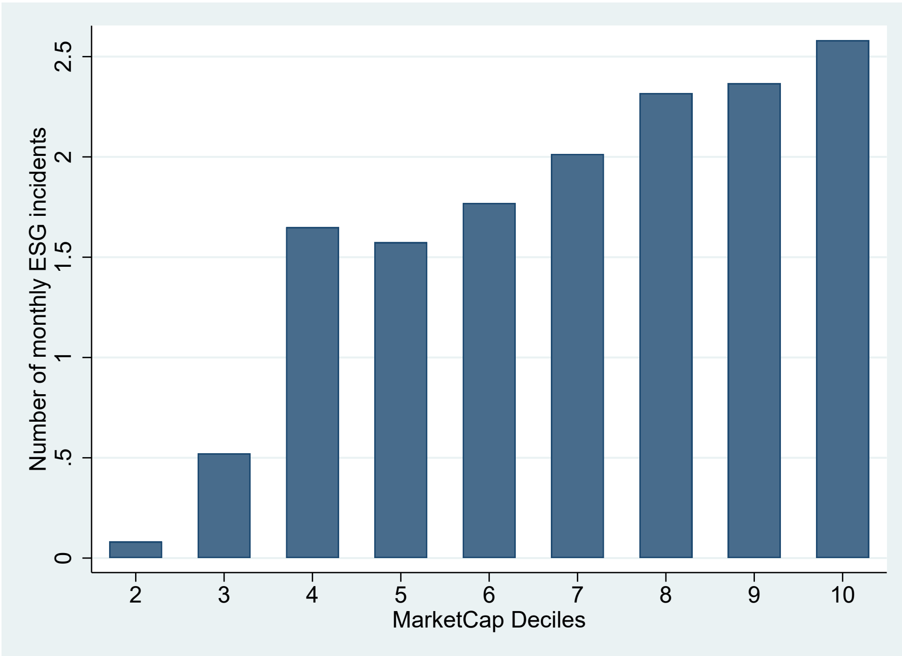


Figure 8: Number of incidents by size

This figure reports the number of incidents by firm size deciles. On the y-axis are the coefficients from the regression equation $num\_incidents_{i,t} = a + \sum_{j=2}^{10} b_j \mathbf{1}\{i \in SizeDecile_j\} + Industry \times month \times country\ FE$, where $num\_incidents_{i,t} + \epsilon_{i,t}$ is the number of RepRisk ESG incidents for firm i in month t. The x-axis shows the deciles based on market capitalization. The omitted decile is the lowest market capitalization decile.



Tables

Table 1: Summary statistics

This table reports the summary statistics of the main variables used in our analysis, from 2008 to 2019. $\Delta EPS/EPS$, $\Delta Sales/Sales$ and $\Delta GrossMargin/GrossMargin$ are the pooled forecast observations over different horizons, from 1 quarter to 3 years.

	Obs.	Mean	SD	p1	p25	p50	p75	p99
$\Delta EPS/EPS$ (%)	2,630,318	-1.24	8.68	-33.33	-1.53	0.00	0.19	21.43
ΔLTG (%)	226,939	-0.11	1.80	-6.23	0.00	0.00	0.00	5.30
$\Delta PTG/PTG$ (%)	604,374	0.24	5.69	-16.67	-0.58	0.00	1.52	16.67
Return (%)	630,118	0.38	9.82	-23.82	-5.08	0.59	6.09	23.29
$\Delta Sales/Sales$ (%)	2,538,492	-0.18	2.23	-7.61	-0.43	0.00	0.19	6.29
$\Delta GrossMargin/GrossMargin$ (%)	1,271,860	-0.13	1.85	-6.78	-0.07	0.00	0.00	5.43
Market Cap. (Bil USD)	7,271,929	10.43	29.92	0.07	0.96	2.75	8.35	139.34
Num. of incidents	7,271,983	0.28	1.22	0.00	0.00	0.00	0.00	5.00
ΔROA(%)	6,568,277	-0.00	0.11	-0.56	0.00	0.00	0.00	0.44
$\Delta(CapEx/Asset)$(%)	7,053,560	-0.00	0.22	-1.10	0.00	0.00	0.00	0.94
$\Delta(NetDebt/Asset)$(%)	7,055,733	0.01	0.56	-2.41	0.00	0.00	0.00	2.71
Any incidents	7,271,983	0.13	0.33	0.00	0.00	0.00	0.00	1.00
Num. of incidents	7,271,983	0.28	1.22	0.00	0.00	0.00	0.00	5.00

Table 2: Reaction of earnings forecasts to ESG incidents

This table reports the results of a regression of changes in consensus EPS forecasts on recent ESG incidents. In columns (1)-(7), the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined as $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the main independent variable takes on a value of one if at least one incident happens in months $[t-6, t]$ and is zero otherwise. In Panel B, the independent variable is defined as one if one incident happens in months $[t-6, t]$, two if more than one incident happens in months $[t-6, t]$, and zero otherwise. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.158**	-0.125*	-0.072	-0.065	-0.110**	-0.143***	-0.150***	-0.005	-0.170***	-0.167***
	(-2.15)	(-1.78)	(-1.08)	(-1.09)	(-2.33)	(-3.39)	(-3.70)	(-0.42)	(-5.89)	(-4.48)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.093	-0.059	0.010	-0.039	-0.069	-0.101**	-0.113***	0.005	-0.133***	-0.160***
	(-1.20)	(-0.79)	(0.15)	(-0.64)	(-1.42)	(-2.36)	(-2.70)	(0.36)	(-4.60)	(-4.29)
>=2 incidents in the past 6 months	-0.302***	-0.273***	-0.253***	-0.125	-0.206***	-0.240***	-0.229***	-0.026*	-0.254***	-0.184***
	(-3.15)	(-2.92)	(-2.68)	(-1.34)	(-3.12)	(-3.98)	(-4.09)	(-1.66)	(-6.30)	(-3.42)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table 3: impact of ESG incidents and other incidents on EPS forecasts

This table reports the results of a regression of the changes in consensus EPS forecasts on ESG incidents and negative key development (KD) incidents. In columns (1)-(3), the dependent variables are changes in the 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$. The first independent variable takes on a value of one if at least one ESG incident happens in months $[t-6, t]$ and is zero otherwise. The second independent variable takes on a value of one if at least one negative KD incident happens in months $[t-6, t]$ and is zero otherwise. Column 4 and Column 5 report the corresponding regression results by pooling the 1- and 2-years and 1- and 3-year forecasts, respectively. The F-statistics and p-values are the results of the hypothesis test that $\beta_{ESG \times h} - \beta_{KD \times h} = 0$. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) 1 year	(2) 2 year	(3) 3 year	(4) 1&2 year	(5) 1&3 year
ESG Incidents=1	-0.106**	-0.140***	-0.145***	-0.106**	-0.106**
	(-2.29)	(-3.39)	(-3.70)	(-2.30)	(-2.30)
KD Negative Incidents in the past 6 months=1	-0.488***	-0.408***	-0.279***	-0.488***	-0.488***
	(-10.25)	(-10.21)	(-7.74)	(-10.34)	(-10.34)
ESG Incidents=1 × 2-year				-0.034	
				(-0.93)	
KD Negative Incidents in the past 6 months=1 × 2-year				0.080**	
				(2.47)	
ESG Incidents=1 × 3-year					-0.039
					(-0.88)
KD Negative Incidents in the past 6 months=1 × 3-year					0.209***
					(4.99)
$\beta_{ESG \times h-year} - \beta_{KD \times h-year}$				-0.114	-0.247
F-stat				5.575	16.284
P value				0.020	0.000
Month × Industry × Country FE	YES	YES	YES	NO	NO
Firm FE	YES	YES	YES	NO	NO
Month × Industry × Country × Horizon FE	NO	NO	NO	YES	YES
Firm × Horizon FE	NO	NO	NO	YES	YES
adj R2	0.075	0.092	0.071	0.083	0.073
Obs.	561492	559144	432938	1120636	994430

Table 4: Reaction of sales and gross margin forecasts to ESG incidents

This table reports the results of a regression of changes in sales and gross margin consensus forecasts on ESG incidents. In columns (1)-(7), the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon sales forecasts, defined by $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{F_{t-1} Sales_{t+h}} \times 100$. In columns (8)-(14), the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon gross margin forecasts, defined as $\frac{F_t GrossMargin_{t+h} - F_{t-1} GrossMargin_{t+h}}{F_{t-1} GrossMargin_{t+h}} \times 100$. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$ and is 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happens in months $[t-6, t]$, as 2 if more than 1 incident happens in months $[t-6, t]$, and as 0 otherwise. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
>=1 incidents in the past 6 months=1	-0.019	-0.037**	-0.040**	-0.021	-0.034***	-0.059***	-0.059***	-0.029	-0.024	0.007	0.020	-0.019	-0.018	0.002
	(-1.19)	(-2.16)	(-2.47)	(-1.33)	(-3.34)	(-4.81)	(-4.58)	(-1.58)	(-1.33)	(0.37)	(1.23)	(-1.65)	(-1.42)	(0.16)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.098	0.096	0.099	0.092	0.105	0.086	0.056	0.046	0.045	0.050	0.060	0.056	0.053
Obs.	279985	251644	224824	131232	552092	541921	417346	131259	119671	105483	61761	296492	286369	181832

Panel B: Splitting by the number of incidents

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
1 incident in the past 6 months	-0.005	-0.014	-0.013	-0.015	-0.025**	-0.041***	-0.038***	-0.033*	-0.019	0.017	0.020	-0.022*	-0.016	0.010
	(-0.33)	(-0.78)	(-0.78)	(-0.86)	(-2.35)	(-3.30)	(-2.65)	(-1.84)	(-1.01)	(0.85)	(1.22)	(-1.69)	(-1.21)	(0.69)
>=2 incidents in the past 6 months	-0.048**	-0.087***	-0.101***	-0.036*	-0.055***	-0.100***	-0.105***	-0.018	-0.037	-0.015	0.019	-0.012	-0.021	-0.015
	(-2.17)	(-4.00)	(-4.50)	(-1.71)	(-3.79)	(-5.80)	(-5.74)	(-0.72)	(-1.55)	(-0.62)	(0.83)	(-0.79)	(-1.31)	(-0.82)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.098	0.096	0.099	0.092	0.105	0.086	0.056	0.046	0.045	0.050	0.060	0.056	0.053
Obs.	279985	251644	224824	131232	552092	541921	417346	131259	119671	105483	61761	296492	286369	181832

Table 5: Dividend discount model and firm valuation

This table reports the results of a regression of several valuation-related variables on ESG incidents. In Columns (1) and (2), the dependent variables are the level or ratio change in the implied discount rate in month t. In Column (3), the dependent variable is the estimated change in firm value resulting from EPS changes only (in %) in month t, defined in Section 5.2. In Column (4), the dependent variable is the cumulative return (in %) over the month t. In Column (5), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. The independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$ and is 0 otherwise. The regression uses only the US sample. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	$\Delta r_{i,t}$	$\frac{\Delta r_{i,t}}{r_{i,t-1}}$	$\frac{\widehat{\Delta PV_{i,t}}}{PV_{i,t-1}}$	$Ret.$	$\frac{\Delta PTG_{i,t}}{PTG_{i,t-1}}$
	(1)	(2)	(3)	(4)	(5)
>=1 incidents in the past 6 months=1	0.000	-0.000	-0.190**	-0.122*	-0.156***
	(0.07)	(-0.20)	(-2.39)	(-1.87)	(-3.15)
Month × Industry FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
adj R2	0.362	0.380	0.039	0.342	0.165
Obs.	160107	160107	160107	160107	160107

Table 6: Variation across regions

This table reports the results of a regression of changes in the consensus EPS and sales forecasts on ESG incidents, interacted with dummies indicating regions. In Panel A, columns (1)-(3), the dependent variables are changes in the 1-year, 2-year, and 3-year horizon consensus EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$. In column (4), the dependent variable is the change in the LTG forecast, defined as $(LTG_t - LTG_{t-1}) \times 100$. In column (5), the dependent variable is the change in the consensus PTG, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (6), the dependent variable is the cumulative return over the month t. In Panel B, the dependent variables are changes in the 1-year, 2-year, and 3-year horizon sales forecasts, defined as $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{F_{t-1} Sales_{t+h}} \times 100$. The baseline category is firms in North America (the US and Canada). $EU15$, $Asia$ and $Others$ are dummies indicating whether a firm is in one of the 15 most developed European countries (defined in Section 6.1), in Asia or in other regions (mostly Australia, Africa and South America). Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: EPS/PTG forecasts and Returns

	(1) 1 year	(2) 2 year	(3) 3 year	(4) LTG	(5) PTG	(6) Return
>=1 incidents in the past 6 months=1	-0.087	-0.126*	-0.236***	-0.009	-0.179***	-0.113*
	(-1.26)	(-1.98)	(-3.72)	(-0.65)	(-3.90)	(-1.84)
>=1 incidents in the past 6 months=1 × EU15	-0.090	-0.110	0.103	0.028	-0.061	-0.193*
	(-0.68)	(-1.01)	(1.06)	(0.80)	(-0.76)	(-1.83)
>=1 incidents in the past 6 months=1 × Asia	-0.062	-0.051	0.149	-0.003	-0.011	-0.092
	(-0.58)	(-0.59)	(1.64)	(-0.09)	(-0.17)	(-1.12)
>=1 incidents in the past 6 months=1 × Others	0.060	0.104	0.204**	-0.015	0.115	-0.037
	(0.43)	(0.77)	(2.01)	(-0.27)	(1.31)	(-0.33)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
adj R2	0.075	0.091	0.071	0.073	0.174	0.363
Obs.	561492	559144	432938	202190	575070	567951

Panel B: Sales forecasts

	(1) 1 year	(2) 2 year	(3) 3 year
>=1 incidents in the past 6 months=1	-0.027*	-0.056***	-0.073***
	(-1.74)	(-3.15)	(-3.70)
>=1 incidents in the past 6 months=1 × EU15	-0.001	-0.025	-0.004
	(-0.02)	(-0.80)	(-0.13)
>=1 incidents in the past 6 months=1 × Asia	-0.015	0.004	0.060**
	(-0.71)	(0.14)	(2.08)
>=1 incidents in the past 6 months=1 × Others	-0.021	-0.003	-0.024
	(-0.63)	(-0.07)	(-0.55)
Month × Industry × Country FE	YES	YES	YES
Firm FE	YES	YES	YES
adj R2	0.092	0.105	0.086
Obs.	552092	541921	417346

Table 7: Interaction with advertising intensity

This table reports the results of a regression of changes in the consensus EPS and sales forecasts on ESG incidents, interacted with advertising intensity. In Panel A, columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, 3-year horizon consensus EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$. In column (8), the dependent variable is the change in the LTG forecast, defined as $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel B, the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, 3-year horizon sales forecasts, defined as $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{F_{t-1} Sales_{t+h}} \times 100$. $highAdIntensity$ is a dummy equal to 1 if the industry's median advertising expenditure (defined as $Advertising\ expenditure/Sales$) is higher than the median for all industries. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: EPS/PTG forecasts and returns

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.103	-0.040	-0.016	-0.110	-0.030	-0.074	-0.147**	-0.011	-0.135***	-0.122**
	(-0.98)	(-0.38)	(-0.16)	(-1.22)	(-0.43)	(-1.23)	(-2.54)	(-0.60)	(-3.57)	(-2.44)
>=1 incidents in the past 6 months=1 × High Ad Intensity	-0.124	-0.172	-0.105	0.094	-0.178**	-0.152*	-0.002	0.008	-0.090*	-0.111
	(-0.92)	(-1.30)	(-0.88)	(0.85)	(-2.15)	(-1.89)	(-0.02)	(0.32)	(-1.85)	(-1.63)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.088	0.089	0.083	0.093	0.075	0.091	0.071	0.073	0.174	0.363
Obs.	282989	262602	242214	147308	561492	559144	432938	202190	575070	567951

Panel B: Sales forecasts

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
>=1 incidents in the past 6 months=1	0.009	-0.014	-0.020	0.019	-0.014	-0.041**	-0.035**
	(0.38)	(-0.50)	(-0.71)	(0.69)	(-0.97)	(-2.48)	(-2.02)
>=1 incidents in the past 6 months=1 × High Ad Intensity	-0.055*	-0.046	-0.040	-0.078**	-0.042**	-0.038*	-0.051**
	(-1.86)	(-1.33)	(-1.13)	(-2.31)	(-2.27)	(-1.80)	(-2.04)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.098	0.096	0.099	0.092	0.105	0.086
Obs.	279985	251644	224824	131232	552092	541921	417346

Table 8: Interaction with firm size

This table reports the results of a regression of changes in the consensus EPS and sales forecasts on ESG incidents, interacted with firm size. In Panel A, columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon consensus EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$. In column (8), the dependent variable is the change in the LTG forecast, defined as $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel B, the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon sales forecasts, defined as $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{F_{t-1} Sales_{t+h}} \times 100$. $LargeFirm$ is a dummy equal to one if the market value of the firm is larger than the median market value from the pooled sample of firms in a given month. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: EPS/PTG forecasts and returns

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.223**	-0.168*	-0.184*	-0.193*	-0.240***	-0.248***	-0.246***	-0.034	-0.241***	-0.228***
	(-2.13)	(-1.71)	(-1.84)	(-1.76)	(-3.94)	(-4.35)	(-3.67)	(-1.23)	(-5.55)	(-3.89)
>=1 incidents in the past 6 months=1 × LargeFirm	0.102	0.073	0.188*	0.204	0.235***	0.189***	0.164**	0.033	0.119**	0.092
	(0.85)	(0.65)	(1.67)	(1.61)	(3.39)	(2.91)	(2.22)	(1.13)	(2.44)	(1.18)
LargeFirm	0.703***	0.742***	0.635***	0.534***	0.691***	0.737***	0.698***	0.031	0.582***	-1.385***
	(6.80)	(7.58)	(6.70)	(5.02)	(11.53)	(12.57)	(10.55)	(1.33)	(9.32)	(-11.02)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.088	0.090	0.084	0.093	0.075	0.092	0.072	0.073	0.175	0.364
Obs.	282988	262599	242214	147308	561484	559135	432934	202190	575066	567948

Panel B: Sales forecasts

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
>=1 incidents in the past 6 months=1	-0.022	-0.036	-0.047*	-0.052**	-0.041***	-0.081***	-0.069***
	(-0.93)	(-1.49)	(-1.87)	(-2.05)	(-3.07)	(-4.36)	(-3.39)
>=1 incidents in the past 6 months=1 × LargeFirm	0.006	-0.002	0.011	0.048*	0.013	0.040*	0.017
	(0.19)	(-0.06)	(0.35)	(1.70)	(0.83)	(1.82)	(0.73)
LargeFirm	0.111***	0.126***	0.134***	0.050*	0.086***	0.156***	0.171***
	(3.97)	(4.53)	(4.52)	(1.70)	(4.87)	(6.80)	(7.05)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.099	0.096	0.099	0.092	0.105	0.086
Obs.	279984	251641	224824	131232	552051	541893	417344

Table 9: Forecast errors and forecast revisions after ESG incidents

This table reports the results of regressions of forecast errors on ESG incidends and forecast revisions. In columns (1)-(3), the dependent variables are the monthly change of EPS forecast errors for 1-3 year horizons, $\Delta FError_t EPS_{i,t+h} = FError_t EPS_{i,t+h} - FError_{t-1} EPS_{i,t+h}$. EPS Forecast errors are defined as $FError_t EPS_{i,t+h} = (\frac{F_t EPS_{t+h} - EPS_{i,t+h}}{EPS_{i,t+h}})^2$. In columns (4)-(6), the dependent variables are the monthly change of sales forecast errors, $\Delta FError_t Sales_{i,t+h} = FError_t Sales_{i,t+h} - FError_{t-1} Sales_{i,t+h}$. Sales forecast errors are defined as $FError_t Sales_{i,t+h} = (\frac{F_t Sales_{t+h} - Sales_{i,t+h}}{Sales_{i,t+h}})^2$. The variable *forecast revision* measures the monthly forecast revisions (EPS or sales), defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$ (columns (1)-(3)), and $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{abs(F_{t-1} Sales_{t+h})} \times 100$ (columns (4)-(6)). The ESG event indicator variable is defined like before, that is as 1 if at least one incident happens in months $[t-6, t]$ and is 0 otherwise. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Δ Forecast Error					
	EPS			Sales		
	(1) 1 year	(2) 2 year	(3) 3 year	(4) 1 year	(5) 2 year	(6) 3 year
>=1 incidents in the past 6 months=1 × forecast revision	0.001**	0.002***	0.003**	0.005	0.020**	0.033***
	(2.05)	(2.79)	(2.41)	(0.82)	(2.23)	(3.40)
>=1 incidents in the past 6 months=1	0.001	-0.004	-0.003	-0.000	0.009*	0.004
	(0.41)	(-1.41)	(-0.90)	(-0.13)	(1.79)	(0.50)
forecast revision	0.016***	0.021***	0.026***	0.102***	0.158***	0.165***
	(23.87)	(26.47)	(31.09)	(16.24)	(13.65)	(14.94)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
adj R2	0.189	0.230	0.260	0.169	0.222	0.204
Obs.	533465	481017	327813	530020	475854	322077

Table 10: ESG sensitivity and forecast precision

This table reports the results of a regression of forecast precision on analyst ESG sensitivity. Forecast precision is defined as the rank of the forecast error in the EPS forecasts, averaged to the analyst-firm level. $ESG\ sensitivity_j$ is the ESG sensitivity of analyst j, defined as the coefficient β^j from the following regression equation: $\frac{\Delta F_t EPS^j}{abs(F_{t-1} EPS^j)} = \alpha + \beta^j \mathbb{1}\{ESG\ incidents\ in\ months\ [t-6, t]\}$. We consider only 1-3 year horizon EPS forecasts when estimating sensitivity. The analyst characteristic control variables include the natural logarithm of the number of years since the first forecast made by the analyst, the natural logarithm of the number of years since the analyst began following the firm, the share of forecasts made for the focal firm out of all forecasts, the natural logarithm of the number of forecasts made per year, and the natural logarithm of the number of firms followed by the analyst. In all the regressions, we control for firm fixed effects. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Forecast precision									
	All		North America		EU15		Asia		Others	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ESG sensitivity	0.024	0.025	0.006	0.010	0.083**	0.089**	0.037	0.041	-0.018	-0.024
	(1.47)	(1.52)	(0.25)	(0.40)	(2.09)	(2.23)	(1.14)	(1.25)	(-0.39)	(-0.52)
Analyst characteristics	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	-0.010	-0.009	-0.014	-0.012	-0.003	-0.000	-0.012	-0.012	-0.005	-0.002
Obs.	68277	67457	31325	30962	13848	13570	16583	16466	6521	6459

Table 11: ESG incidents predict ESG scores

This table reports the results of a regression of ESG scores on ESG incidents. In columns (1)-(3), the dependent variables are the ESG scores. In columns (4)-(6), the dependent variables are the natural logarithm of the ESG scores. All the ESG scores are on a 0-100 scale. The independent variable is the natural log of the number of incidents in the past 12 months. The F-statistic and p-value are the results of a test for whether the sum of the coefficients is equal to 0. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	ESG Score			log(ESG Score)		
	(1) Asset4	(2) MSCI	(3) Sustainalytics	(4) Asset4	(5) MSCI	(6) Sustainalytics
log(num. incidents) in month t	-0.698***	-0.778***	-0.031	-0.018***	-0.023***	-0.001**
	(-9.63)	(-8.50)	(-1.06)	(-8.95)	(-5.97)	(-2.27)
log(num. incidents) in month t-1	-0.689***	-0.758***	-0.078***	-0.018***	-0.022***	-0.002***
	(-9.44)	(-8.29)	(-2.70)	(-8.92)	(-5.97)	(-3.91)
log(num. incidents) in month t-2	-0.656***	-0.749***	-0.061**	-0.017***	-0.023***	-0.002***
	(-8.94)	(-8.10)	(-2.12)	(-8.47)	(-6.05)	(-3.20)
log(num. incidents) in month t-3	-0.656***	-0.777***	-0.058**	-0.017***	-0.022***	-0.001***
	(-8.85)	(-8.50)	(-2.03)	(-8.53)	(-5.68)	(-3.04)
log(num. incidents) in month t-4	-0.630***	-0.787***	-0.046	-0.017***	-0.021***	-0.001***
	(-8.51)	(-8.53)	(-1.59)	(-8.34)	(-5.55)	(-2.62)
log(num. incidents) in month t-5	-0.620***	-0.831***	-0.066**	-0.017***	-0.024***	-0.001***
	(-8.25)	(-9.03)	(-2.30)	(-8.40)	(-6.15)	(-3.15)
log(num. incidents) in month t-6	-0.625***	-0.839***	-0.069**	-0.017***	-0.024***	-0.001***
	(-8.28)	(-9.00)	(-2.38)	(-8.52)	(-6.11)	(-3.18)
log(num. incidents) in month t-7	-0.641***	-0.826***	-0.057**	-0.018***	-0.023***	-0.001***
	(-8.42)	(-8.99)	(-1.99)	(-8.88)	(-6.13)	(-2.94)
log(num. incidents) in month t-8	-0.693***	-0.888***	-0.064**	-0.020***	-0.026***	-0.002***
	(-9.08)	(-9.54)	(-2.23)	(-9.75)	(-6.63)	(-3.22)
log(num. incidents) in month t-9	-0.756***	-0.913***	-0.061**	-0.022***	-0.025***	-0.002***
	(-9.84)	(-9.81)	(-2.11)	(-10.69)	(-6.55)	(-3.19)
log(num. incidents) in month t-10	-0.794***	-0.995***	-0.056*	-0.023***	-0.029***	-0.001***
	(-10.31)	(-10.78)	(-1.92)	(-11.26)	(-7.47)	(-3.01)
log(num. incidents) in month t-11	-0.855***	-1.059***	-0.082***	-0.026***	-0.031***	-0.002***
	(-10.94)	(-11.49)	(-2.81)	(-12.19)	(-8.01)	(-3.97)
log(num. incidents) in month t-12	-0.905***	-1.147***	-0.120***	-0.027***	-0.031***	-0.003***
	(-11.51)	(-12.15)	(-4.04)	(-13.01)	(-7.90)	(-5.34)
Month * Industry FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Sum of Coef.	-9.218	-11.347	-0.848	-0.257	-0.324	-0.020
F-stat	2446.512	1518.354	97.192	2541.480	1025.616	177.873
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Adj. R2	0.888	0.763	0.901	0.867	0.667	0.902
Obs.	301221	262104	169691	301221	262104	169691

Internet appendix

Table IA1: List of ESG issues

This table reports the issues that RepRisk retains and their corresponding categories. One RepRisk incident could be associated with multiple issues.

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

Table IA2: Distribution of ESG incidents by type

This table reports the distribution of ESG incidents by type. E, S and G indicate environment, social, and governance incidents, respectively.

E	S	G	# incidents	Percent
1	0	0	4,023	5.26
0	1	0	27,663	36.14
0	0	1	6,427	8.40
1	1	0	14,771	19.30
1	0	1	431	0.56
0	1	1	21,037	27.48
1	1	1	2,186	2.86

Table IA3: Distribution of observations across countries

This table reports the number of observations by country. Columns (1), (3), and (5) present the number of observations for the full sample, the sample of annual forecasts (including PTGs and LTG), and the sample of quarterly forecasts. Columns (2), (4), and (6) present the corresponding percentage out of all countries.

	(1)	(2)	(3)	(4)	(5)	(6)
Country	Obs. Total	Perc. Total (%)	Obs. Annual	Perc. Annual (%)	Obs. Quarter	Perc. Quarter (%)
USA	3,245,071	44.62	1,618,025	32.98	1,627,046	68.76
JPN	568,763	7.82	483,811	9.86	84,952	3.59
KOR	341,933	4.70	217,925	4.44	124,008	5.24
CAN	334,948	4.61	198,425	4.04	136,523	5.77
GBR	277,493	3.82	270,154	5.51	7,339	0.31
IND	238,486	3.28	214,822	4.38	23,664	1.00
TWN	209,607	2.88	109,099	2.22	100,508	4.25
DEU	146,460	2.01	118,928	2.42	27,532	1.16
BRA	133,017	1.83	96,463	1.97	36,554	1.54
AUS	121,895	1.68	121,697	2.48	198	0.01
CYM	114,685	1.58	106,467	2.17	8,218	0.35
FRA	113,790	1.56	108,610	2.21	5,180	0.22
CHE	91,463	1.26	81,308	1.66	10,155	0.43
MYS	89,619	1.23	87,071	1.77	2,548	0.11
NOR	83,264	1.14	52,696	1.07	30,568	1.29
ESP	71,904	0.99	64,903	1.32	7,001	0.30
IDN	66,383	0.91	63,014	1.28	3,369	0.14
HKG	65,531	0.90	63,324	1.29	2,207	0.09
ZAF	64,527	0.89	63,130	1.29	1,397	0.06
SWE	63,175	0.87	41,071	0.84	22,104	0.93
BMU	61,782	0.85	58,722	1.20	3,060	0.13
ITA	61,459	0.85	56,826	1.16	4,633	0.20
NLD	57,997	0.80	49,555	1.01	8,442	0.36
FIN	57,669	0.79	36,032	0.73	21,637	0.91
CHN	56,398	0.78	54,492	1.11	1,906	0.08
MEX	52,145	0.72	37,228	0.76	14,917	0.63
DNK	51,316	0.71	35,352	0.72	15,964	0.67
SGP	47,736	0.66	43,983	0.90	3,753	0.16
PHL	43,567	0.60	40,998	0.84	2,569	0.11
TUR	35,764	0.49	32,297	0.66	3,467	0.15
BEL	32,986	0.45	30,245	0.62	2,741	0.12
POL	31,081	0.43	29,535	0.60	1,546	0.07
AUT	27,983	0.38	23,943	0.49	4,040	0.17
NZL	24,393	0.34	24,393	0.50	0	0.00
RUS	22,828	0.31	22,341	0.46	487	0.02
CHL	19,836	0.27	16,333	0.33	3,503	0.15
NGA	19,235	0.26	19,212	0.39	23	0.00
PRT	19,206	0.26	17,591	0.36	1,615	0.07
ISR	19,204	0.26	15,261	0.31	3,943	0.17
THA	18,999	0.26	17,549	0.36	1,450	0.06
PAK	16,315	0.22	16,116	0.33	199	0.01
GRC	15,868	0.22	14,793	0.30	1,075	0.05
IRL	15,816	0.22	14,629	0.30	1,187	0.05
LUX	15,751	0.22	12,889	0.26	2,862	0.12
ARG	4,635	0.06	4,550	0.09	85	0.00

Table IA4: Auto-correlation of ESG incidents

This table reports the results of regressions of number of ESG incidents on number of ESG incidents in earlier months. The dependent variable is the natural logarithm of 1 + number of ESG incidents in month t. The independent variables are the natural logarithm of 1 + number of ESG incidents in months $t-1$, $t-2$, $t-3$, $t-4$, $t-5$, $t-6$. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	log(1+num incidents) in month t					
	(1)	(2)	(3)	(4)	(5)	(6)
log(1+num incidents) in month t-1	0.171***	0.146***	0.128***	0.116***	0.107***	0.102***
	(15.68)	(17.43)	(18.67)	(19.44)	(19.60)	(20.03)
log(1+num incidents) in month t-2		0.146***	0.128***	0.115***	0.106***	0.100***
		(16.92)	(18.03)	(18.93)	(19.16)	(19.14)
log(1+num incidents) in month t-3			0.124***	0.111***	0.101***	0.094***
			(17.62)	(18.05)	(18.65)	(19.13)
log(1+num incidents) in month t-4				0.099***	0.089***	0.081***
				(17.28)	(17.10)	(16.88)
log(1+num incidents) in month t-5					0.085***	0.076***
					(15.29)	(14.86)
log(1+num incidents) in month t-6						0.072***
						(14.24)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
adj R2	0.564	0.573	0.580	0.584	0.587	0.589
Obs.	695084	695084	695084	695084	695084	695084

Table IA5: Reaction of earnings forecasts to ESG incidents—Different lags

This table reports the results of a regression of the changes in EPS forecasts on ESG incidents. In columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-3, t]$, and 0 otherwise. In Panel B, the independent variable is defined as 1 if at least one incident happens in months $[t-9, t]$ and is 0 otherwise. In Panel C, the independent variable is defined as 1 if at least one incident happens in months $[t-12, t]$ and is 0 otherwise. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Incidents with a 3-month lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 3 months=1	-0.102	-0.136**	-0.076	0.013	-0.136***	-0.134***	-0.153***	-0.013	-0.157***	-0.205***
	(-1.36)	(-2.09)	(-1.21)	(0.19)	(-2.93)	(-3.04)	(-3.61)	(-1.00)	(-5.72)	(-5.19)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Incidents with a 9-month lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 9 months=1	-0.101	-0.116*	-0.052	-0.041	-0.134***	-0.155***	-0.175***	-0.014	-0.165***	-0.185***
	(-1.35)	(-1.70)	(-0.74)	(-0.64)	(-2.95)	(-3.74)	(-4.33)	(-1.10)	(-5.69)	(-4.80)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Incidents with a 12-month lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 12 months=1	-0.060	-0.120*	-0.021	0.005	-0.130***	-0.155***	-0.173***	-0.011	-0.168***	-0.171***
	(-0.80)	(-1.70)	(-0.30)	(0.09)	(-2.83)	(-3.74)	(-4.10)	(-0.81)	(-5.90)	(-4.27)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA6: Reaction of earnings forecasts to ESG incidents—Time-varying controls

This table reports the results of a regression of the changes in EPS forecasts on ESG incidents. In columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$ and is 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happens in months $[t-6, t]$, as 2 if more than 1 incident happen in months $[t-6, t]$, and as 0 otherwise. *Quintile MarketCap* are the market capitalization quintiles for a given month. *Quintile B/M Ratio* are the book-to-market ratio quintiles for a given month. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.138*	-0.108	-0.058	-0.054	-0.102**	-0.130***	-0.144***	-0.005	-0.161***	-0.170***
	(-1.96)	(-1.57)	(-0.90)	(-0.93)	(-2.22)	(-3.18)	(-3.71)	(-0.46)	(-5.79)	(-4.64)
Quintile MarketCap=2	0.514***	0.611***	0.510***	0.315***	0.522***	0.511***	0.601***	0.059***	0.418***	-1.506***
	(3.62)	(4.39)	(3.41)	(2.63)	(3.97)	(3.74)	(4.82)	(2.71)	(5.30)	(-8.82)
Quintile MarketCap=3	-0.029	0.463	0.433	0.861**	0.658***	0.538**	1.071***	0.028	0.696***	-2.363***
	(-0.08)	(1.34)	(1.52)	(2.54)	(2.78)	(2.24)	(4.37)	(0.56)	(5.23)	(-9.32)
Quintile MarketCap=4	1.101**	1.352***	1.321***	2.386***	1.505***	1.242***	1.534***	0.037	1.172***	-3.404***
	(2.13)	(2.88)	(2.69)	(4.31)	(5.48)	(4.66)	(5.73)	(0.52)	(7.07)	(-10.48)
Quintile MarketCap=5	1.458**	1.909***	1.419**	3.138***	2.242***	1.846***	1.939***	-0.020	1.684***	-4.550***
	(2.35)	(3.29)	(2.43)	(4.88)	(7.04)	(6.11)	(6.30)	(-0.25)	(8.50)	(-11.86)
Quintile B/M Ratio=2	-0.780***	-0.907***	-0.810***	-0.664**	-1.356***	-1.416***	-1.083***	-0.010	-0.850***	0.467***
	(-2.99)	(-3.56)	(-3.54)	(-2.01)	(-11.32)	(-11.48)	(-10.48)	(-0.28)	(-12.58)	(4.26)
Quintile B/M Ratio=3	-0.547	-0.714**	-0.169	-0.203	-1.646***	-1.717***	-1.154***	0.013	-1.258***	0.585***
	(-1.62)	(-2.25)	(-0.55)	(-0.54)	(-9.39)	(-10.25)	(-7.27)	(0.22)	(-12.24)	(3.76)
Quintile B/M Ratio=4	-0.697***	-0.607**	-0.486**	-0.486**	-1.700***	-1.537***	-1.177***	-0.037	-1.384***	0.779***
	(-2.84)	(-2.46)	(-2.03)	(-2.02)	(-7.52)	(-6.60)	(-5.11)	(-0.80)	(-10.28)	(4.06)
Quintile B/M Ratio=5	-2.257***	-2.035***	-1.705***	-1.342***	-3.022***	-2.944***	-2.229***	-0.019	-2.385***	1.575***
	(-8.14)	(-7.63)	(-6.45)	(-5.37)	(-11.52)	(-11.06)	(-8.94)	(-0.37)	(-14.50)	(5.69)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.092	0.087	0.097	0.079	0.096	0.075	0.073	0.178	0.366
Obs.	278760	259008	239098	145417	546317	544152	420869	199237	559192	552951

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.088	-0.053	0.013	-0.037	-0.070	-0.095**	-0.113***	0.005	-0.129***	-0.158***
	(-1.16)	(-0.73)	(0.20)	(-0.61)	(-1.46)	(-2.26)	(-2.80)	(0.36)	(-4.55)	(-4.30)
>=2 incidents in the past 6 months	-0.251***	-0.231**	-0.215**	-0.093	-0.179***	-0.210***	-0.211***	-0.027*	-0.236***	-0.197***
	(-2.68)	(-2.49)	(-2.31)	(-1.00)	(-2.72)	(-3.57)	(-3.81)	(-1.74)	(-6.03)	(-3.65)
Quintile MarketCap=2	0.512***	0.609***	0.507***	0.314***	0.521***	0.510***	0.600***	0.059***	0.416***	-1.506***
	(3.60)	(4.37)	(3.39)	(2.63)	(3.96)	(3.73)	(4.81)	(2.70)	(5.28)	(-8.83)
Quintile MarketCap=3	-0.028	0.464	0.434	0.862**	0.658***	0.538**	1.072***	0.028	0.696***	-2.363***
	(-0.08)	(1.35)	(1.53)	(2.55)	(2.78)	(2.24)	(4.37)	(0.56)	(5.23)	(-9.32)
Quintile MarketCap=4	1.094**	1.344***	1.310***	2.383***	1.503***	1.239***	1.533***	0.036	1.170***	-3.405***
	(2.12)	(2.86)	(2.67)	(4.30)	(5.48)	(4.65)	(5.73)	(0.51)	(7.06)	(-10.48)
Quintile MarketCap=5	1.458**	1.909***	1.423**	3.139***	2.240***	1.843***	1.938***	-0.020	1.682***	-4.551***
	(2.35)	(3.29)	(2.44)	(4.89)	(7.04)	(6.10)	(6.30)	(-0.24)	(8.49)	(-11.87)
Quintile B/M Ratio=2	-0.779***	-0.906***	-0.808***	-0.664**	-1.356***	-1.416***	-1.082***	-0.010	-0.850***	0.467***
	(-2.98)	(-3.55)	(-3.54)	(-2.00)	(-11.32)	(-11.48)	(-10.48)	(-0.27)	(-12.58)	(4.26)
Quintile B/M Ratio=3	-0.547	-0.714**	-0.169	-0.203	-1.646***	-1.717***	-1.153***	0.013	-1.258***	0.585***
	(-1.62)	(-2.26)	(-0.55)	(-0.54)	(-9.39)	(-10.24)	(-7.27)	(0.22)	(-12.25)	(3.76)
Quintile B/M Ratio=4	-0.696***	-0.606**	-0.484**	-0.485**	-1.699***	-1.536***	-1.176***	-0.036	-1.383***	0.779***
	(-2.84)	(-2.46)	(-2.02)	(-2.02)	(-7.51)	(-6.59)	(-5.10)	(-0.78)	(-10.27)	(4.06)
Quintile B/M Ratio=5	-2.254***	-2.032***	-1.701***	-1.342***	-3.020***	-2.942***	-2.226***	-0.018	-2.383***	1.575***
	(-8.13)	(-7.63)	(-6.43)	(-5.37)	(-11.51)	(-11.05)	(-8.93)	(-0.35)	(-14.49)	(5.69)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.092	0.087	0.097	0.079	0.096	0.075	0.073	0.178	0.366
Obs.	278760	259008	239098	145417	546317	544152	420869	199237	559192	552951

Table IA7: Reaction of earnings forecasts to ESG incidents—No firm fixed effects

This table reports the results of a regression of the changes in EPS forecasts on ESG incidents. In columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$ and is 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happens in months $[t-6, t]$, as 2 if more than 1 incident happens in months $[t-6, t]$, and as 0 otherwise. *Quintile MarketCap* are the market capitalization quintiles for a given month. *Quintile B/M Ratio* are the book-to-market ratio quintiles for a given month. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.358***	-0.196***	-0.132**	-0.169***	-0.310***	-0.252***	-0.220***	-0.011	-0.270***	-0.168***
	(-5.54)	(-3.09)	(-2.23)	(-2.92)	(-6.82)	(-6.37)	(-6.09)	(-1.16)	(-10.55)	(-3.56)
Quintile MarketCap=2	1.257***	1.034***	0.747***	0.326***	0.989***	0.861***	0.844***	0.052***	0.391***	0.061
	(10.51)	(11.73)	(9.46)	(4.99)	(12.02)	(11.41)	(9.76)	(4.46)	(8.28)	(0.50)
Quintile MarketCap=3	1.268***	1.236***	1.068***	0.731**	1.913***	1.616***	1.711***	0.089***	1.002***	0.731***
	(4.15)	(4.57)	(4.30)	(2.61)	(10.73)	(9.15)	(9.93)	(3.13)	(11.18)	(3.36)
Quintile MarketCap=4	2.520***	2.360***	1.945***	1.415***	2.871***	2.347***	2.276***	0.143***	1.404***	0.956***
	(6.82)	(7.04)	(6.06)	(3.81)	(14.42)	(12.13)	(12.34)	(3.82)	(13.21)	(3.44)
Quintile MarketCap=5	3.031***	2.850***	2.287***	1.861***	3.520***	2.884***	2.662***	0.139***	1.853***	1.112***
	(7.15)	(7.23)	(6.31)	(4.33)	(16.07)	(13.72)	(12.89)	(2.90)	(15.16)	(3.48)
Quintile B/M Ratio=2	-0.921***	-0.790***	-0.689***	-0.661***	-1.062***	-1.050***	-0.871***	-0.030	-0.666***	-0.072
	(-4.25)	(-3.83)	(-3.75)	(-2.66)	(-9.81)	(-10.80)	(-10.08)	(-1.31)	(-12.29)	(-0.77)
Quintile B/M Ratio=3	-0.648**	-0.603**	-0.138	0.093	-1.172***	-1.150***	-0.842***	-0.029	-1.002***	-0.311**
	(-2.48)	(-2.45)	(-0.59)	(0.31)	(-8.12)	(-8.65)	(-6.43)	(-0.75)	(-11.92)	(-2.26)
Quintile B/M Ratio=4	-0.076	0.044	0.115	0.127	-0.575***	-0.426**	-0.332**	-0.041	-0.678***	-0.041
	(-0.35)	(0.23)	(0.70)	(0.83)	(-3.20)	(-2.36)	(-2.02)	(-1.59)	(-5.94)	(-0.32)
Quintile B/M Ratio=5	-1.431***	-1.026***	-0.733***	-0.369**	-1.514***	-1.273***	-0.813***	-0.040	-1.423***	-0.068
	(-5.98)	(-5.11)	(-4.13)	(-2.27)	(-7.57)	(-6.31)	(-4.61)	(-1.57)	(-11.07)	(-0.38)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
adj R2	0.067	0.075	0.073	0.081	0.054	0.076	0.062	0.079	0.170	0.361
Obs.	278844	259080	239173	145643	546383	544202	420981	199335	559239	552995

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.192***	-0.063	0.007	-0.112*	-0.196***	-0.171***	-0.151***	-0.002	-0.191***	-0.165***
	(-2.78)	(-0.91)	(0.11)	(-1.90)	(-4.31)	(-4.17)	(-3.83)	(-0.13)	(-7.35)	(-4.11)
>=2 incidents in the past 6 months	-0.515***	-0.320***	-0.260***	-0.222***	-0.423***	-0.334***	-0.284***	-0.019*	-0.350***	-0.171***
	(-5.84)	(-3.88)	(-3.40)	(-2.82)	(-6.82)	(-6.24)	(-6.05)	(-1.81)	(-10.26)	(-2.63)
Quintile MarketCap=2	1.295***	1.064***	0.778***	0.339***	1.017***	0.881***	0.861***	0.054***	0.410***	0.062
	(10.88)	(12.04)	(9.70)	(5.11)	(12.26)	(11.60)	(9.94)	(4.64)	(8.62)	(0.51)
Quintile MarketCap=3	1.373***	1.324***	1.165***	0.773***	1.962***	1.652***	1.744***	0.096***	1.037***	0.732***
	(4.49)	(4.92)	(4.64)	(2.74)	(10.93)	(9.37)	(10.09)	(3.38)	(11.58)	(3.41)
Quintile MarketCap=4	2.656***	2.473***	2.070***	1.471***	2.948***	2.404***	2.327***	0.153***	1.458***	0.958***
	(7.22)	(7.41)	(6.46)	(4.00)	(14.70)	(12.47)	(12.55)	(4.06)	(13.62)	(3.50)
Quintile MarketCap=5	3.206***	2.992***	2.444***	1.930***	3.611***	2.951***	2.722***	0.151***	1.918***	1.114***
	(7.58)	(7.65)	(6.71)	(4.52)	(16.40)	(14.08)	(13.08)	(3.13)	(15.58)	(3.53)
Quintile B/M Ratio=2	-0.914***	-0.785***	-0.683***	-0.658***	-1.057***	-1.046***	-0.867***	-0.029	-0.663***	-0.072
	(-4.23)	(-3.80)	(-3.73)	(-2.65)	(-9.78)	(-10.79)	(-10.04)	(-1.28)	(-12.27)	(-0.77)
Quintile B/M Ratio=3	-0.648**	-0.605**	-0.141	0.091	-1.167***	-1.147***	-0.839***	-0.028	-0.998***	-0.311**
	(-2.48)	(-2.46)	(-0.61)	(0.31)	(-8.09)	(-8.64)	(-6.42)	(-0.74)	(-11.90)	(-2.26)
Quintile B/M Ratio=4	-0.074	0.045	0.116	0.127	-0.569***	-0.422**	-0.329**	-0.041	-0.674***	-0.041
	(-0.34)	(0.24)	(0.71)	(0.84)	(-3.17)	(-2.34)	(-2.00)	(-1.58)	(-5.92)	(-0.32)
Quintile B/M Ratio=5	-1.421***	-1.018***	-0.724***	-0.365**	-1.500***	-1.263***	-0.804***	-0.039	-1.413***	-0.068
	(-5.95)	(-5.08)	(-4.09)	(-2.25)	(-7.52)	(-6.27)	(-4.58)	(-1.54)	(-11.02)	(-0.38)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
adj R2	0.067	0.075	0.073	0.081	0.054	0.076	0.062	0.079	0.170	0.361
Obs.	278844	259080	239173	145643	546383	544202	420981	199335	559239	552995

Table IA8: Reaction of earnings forecasts to ESG incidents—Controlling for fundamentals

This table reports the results of a regression of the changes in EPS forecasts on ESG incidents. In columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$ and is 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happens in months $[t-6, t]$, as 2 if more than 1 incident happens in months $[t-6, t]$, and as 0 otherwise. Other variables are defined as $\Delta ROA_t = ROA_t - ROA_{t-1}$, $\Delta(\frac{Capx}{Asset})_t = (\frac{Capx}{Asset})_t - (\frac{Capx}{Asset})_{t-1}$ and $\Delta(\frac{NetDebt}{Asset})_t = (\frac{NetDebt}{Asset})_t - (\frac{NetDebt}{Asset})_{t-1}$. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.178**	-0.102	-0.062	-0.071	-0.085*	-0.135***	-0.163***	-0.015	-0.167***	-0.146***
	(-2.38)	(-1.38)	(-0.92)	(-1.16)	(-1.68)	(-2.99)	(-3.91)	(-1.06)	(-5.55)	(-3.72)
Δ ROA	1.792***	1.466***	1.204***	1.377***	1.641***	1.299***	0.868***	-0.507***	0.663***	0.694***
	(8.96)	(8.43)	(7.25)	(2.68)	(13.91)	(12.59)	(6.02)	(-9.38)	(10.31)	(8.63)
Δ CapEx/Asset	-0.078	0.136	0.205	0.489	0.157	0.081	0.180	0.016	-0.315***	-0.273**
	(-0.22)	(0.55)	(0.78)	(0.52)	(1.03)	(0.52)	(0.68)	(0.25)	(-3.23)	(-2.33)
Δ NetDebt/Asset	-0.154**	-0.109**	-0.049	-0.052	-0.097***	-0.080**	-0.088	-0.010	-0.115***	-0.125***
	(-2.50)	(-2.21)	(-0.87)	(-0.29)	(-3.00)	(-2.33)	(-1.43)	(-0.87)	(-4.77)	(-4.02)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.094	0.087	0.096	0.079	0.097	0.073	0.074	0.167	0.347
Obs.	257527	239940	222268	136370	476711	475173	364748	174307	485043	478838

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.113	-0.043	0.010	-0.044	-0.043	-0.086*	-0.120***	-0.004	-0.127***	-0.139***
	(-1.45)	(-0.56)	(0.16)	(-0.70)	(-0.81)	(-1.88)	(-2.76)	(-0.26)	(-4.21)	(-3.54)
>=2 incidents in the past 6 months	-0.322***	-0.233**	-0.222**	-0.131	-0.183**	-0.246***	-0.254***	-0.037**	-0.260***	-0.162***
	(-3.22)	(-2.37)	(-2.28)	(-1.38)	(-2.59)	(-3.80)	(-4.38)	(-2.14)	(-6.10)	(-2.79)
Δ ROA	1.792***	1.466***	1.204***	1.376***	1.641***	1.298***	0.868***	-0.507***	0.663***	0.694***
	(8.97)	(8.43)	(7.26)	(2.67)	(13.91)	(12.59)	(6.02)	(-9.38)	(10.30)	(8.63)
Δ CapEx/Asset	-0.078	0.135	0.204	0.488	0.157	0.082	0.181	0.016	-0.315***	-0.273**
	(-0.22)	(0.55)	(0.78)	(0.52)	(1.03)	(0.52)	(0.68)	(0.25)	(-3.23)	(-2.33)
Δ NetDebt/Asset	-0.154**	-0.108**	-0.048	-0.052	-0.097***	-0.079**	-0.088	-0.010	-0.115***	-0.125***
	(-2.50)	(-2.21)	(-0.87)	(-0.28)	(-3.00)	(-2.33)	(-1.43)	(-0.87)	(-4.77)	(-4.01)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.094	0.087	0.096	0.079	0.097	0.073	0.074	0.167	0.347
Obs.	257527	239940	222268	136370	476711	475173	364748	174307	485043	478838

Table IA9: Impact on earnings forecasts by type of negative event

This table reports the impact of different types of negative events on earnings forecasts across the 1- to 3-year horizons. For each event type u and horizon h, we estimate the regression equation $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta \mathbb{1}\{type\ u\ incidents\ in\ [t-6,t]\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$, where the dependent variable is the change in the EPS forecasts scaled by the lagged absolute value of the EPS forecasts. The independent variable is one if an event of type u happens in months $[t-6,t]$. The numbers in the table are the estimated βs for each type of event u and forecast horizon h. Results are in %.

Event	1-year horizon	2-year horizon	3-year horizon
ESG Incidents	-0.11	-0.14	-0.15
Announcement of Operating Results	-0.35	-0.25	-0.28
Announcements of Sales/Trading Statement	-0.12	-0.20	-0.07
Business Reorganizations	-0.28	-0.14	-0.15
Changes in Company By laws/Rules	-0.12	-0.06	-0.01
Considering Multiple Strategic Alternatives	-0.93	-0.84	-0.45
Corporate Guidance - Lowered	-2.03	-1.70	-1.32
Credit Rating - CreditWatch/Outlook Action	-0.47	-0.40	-0.26
Credit Rating - Downgrade	-1.51	-1.40	-0.84
Credit Rating - New Rating	-0.28	-0.23	-0.01
Debt Financing Related	-0.14	-0.00	0.04
Delayed SEC Filings	-0.97	-1.00	-0.65
Discontinued Operations/Downsizings	-0.57	-0.47	-0.37
Dividend Decreases	-0.94	-0.80	-0.47
Executive Changes - CEO	-0.50	-0.40	-0.34
Executive Changes - CFO	-0.28	-0.32	-0.23
Fixed Income Offerings	-0.23	-0.10	-0.03
Follow-on Equity Offerings	-0.17	-0.20	-0.20
Guidance/Update Calls	-1.08	-1.01	-0.74
Halt/Resume of Operations - Unusual Events	-0.87	-0.75	-0.43
Impairments/Write Offs	-0.39	-0.26	-0.04
Index Constituent Drops	-0.20	-0.19	-0.13
Interim Management Statement Release	-0.35	-0.39	-0.15
Labor-related Announcements	-0.26	-0.24	-0.13
Lawsuits & Legal Issues	-0.33	-0.25	-0.21
M&A Rumors and Discussions	-0.30	-0.30	-0.25
Potential Buyback	-0.16	0.09	0.01
Regulatory Agency Inquiries	-0.38	-0.40	-0.32
Restatements of Operating Results	-0.54	-0.28	-0.12
Sales/Trading Statement Calls	-0.37	-0.51	-0.47
Seeking Financing/Partners	-0.26	-0.22	-0.05
Seeking to Sell/Divest	-0.24	-0.33	-0.30
Special Calls	-0.23	-0.15	-0.14
Special Shareholders Meeting	-0.19	-0.06	-0.00

Table IA10: Reaction of earnings forecasts to ESG incidents—By E/S/G category

This table reports the results of a regression of the changes in EPS forecasts on ESG incidents. In columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_tEPS_{t+h}-F_{t-1}EPS_{t+h}}{abs(F_{t-1}EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t-PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variable is defined as 1 if any environmental incidents happen in months $[t-6, t]$ and is 0 otherwise. In Panel B, the independent variable is defined as 1 if any social incidents happen in months $[t-6, t]$ and is 0 otherwise. In Panel C, the independent variable is defined as 1 if any governance incidents happen in months $[t-6, t]$ and is 0 otherwise. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Environmental incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 E incidents in the past 6 months=1	-0.141	-0.047	-0.213**	-0.138	-0.065	-0.090	-0.083	0.013	-0.093***	-0.091*
	(-1.36)	(-0.50)	(-2.21)	(-1.43)	(-1.00)	(-1.41)	(-1.35)	(0.75)	(-2.67)	(-1.74)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Social incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 S incidents in the past 6 months=1	-0.165**	-0.205***	-0.116*	-0.093	-0.164***	-0.191***	-0.168***	-0.005	-0.166***	-0.131***
	(-2.22)	(-3.01)	(-1.73)	(-1.44)	(-3.66)	(-4.64)	(-4.07)	(-0.42)	(-5.68)	(-3.46)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Governance incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 G incidents in the past 6 months=1	-0.127	-0.038	0.012	0.017	-0.115**	-0.084*	-0.107**	-0.012	-0.137***	-0.137***
	(-1.59)	(-0.47)	(0.14)	(0.22)	(-2.29)	(-1.85)	(-2.34)	(-0.85)	(-3.84)	(-3.14)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA11: Reaction of earnings forecasts to ESG incidents—By E/S/G category

This table reports the results of a regression of the changes in EPS forecasts on ESG incidents. In columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variable is defined as 1 if 1 environmental incident happens in months $[t-6, t]$, as 2 if more than 1 environmental incident happens in months $[t-6, t]$, and as 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 social incident happens in months $[t-6, t]$, as 2 if more than 1 social incident happens in months $[t-6, t]$, and as 0 otherwise. In Panel C, the independent variable is defined as 1 if 1 governance incident happens in months $[t-6, t]$, as 2 if more than 1 governance incident happens in months $[t-6, t]$, and as 0 otherwise. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Environmental incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 E incident in the past 6 months	-0.071	0.017	-0.187*	-0.063	-0.049	-0.046	-0.064	0.029	-0.060*	-0.081
	(-0.67)	(0.17)	(-1.91)	(-0.65)	(-0.76)	(-0.70)	(-1.03)	(1.61)	(-1.70)	(-1.47)
>=2 E incidents in the past 6 months	-0.319**	-0.209	-0.279*	-0.325**	-0.109	-0.210**	-0.134	-0.028	-0.186***	-0.121
	(-2.06)	(-1.43)	(-1.92)	(-2.10)	(-1.04)	(-2.30)	(-1.43)	(-1.16)	(-3.41)	(-1.61)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Social incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 S incident in the past 6 months	-0.101	-0.136*	-0.034	-0.031	-0.121***	-0.152***	-0.141***	0.008	-0.134***	-0.131***
	(-1.27)	(-1.87)	(-0.51)	(-0.46)	(-2.63)	(-3.45)	(-3.24)	(0.59)	(-4.49)	(-3.43)
>=2 S incidents in the past 6 months	-0.308***	-0.355***	-0.296***	-0.228**	-0.260***	-0.277***	-0.224***	-0.030*	-0.238***	-0.131**
	(-3.16)	(-3.82)	(-3.05)	(-2.54)	(-3.94)	(-4.56)	(-4.05)	(-1.85)	(-5.86)	(-2.43)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Governance incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 G incident in the past 6 months	-0.088	0.019	0.054	0.050	-0.058	-0.050	-0.104**	-0.010	-0.133***	-0.174***
	(-1.11)	(0.23)	(0.64)	(0.60)	(-1.13)	(-1.06)	(-2.07)	(-0.65)	(-3.56)	(-3.94)
>=2 G incidents in the past 6 months	-0.222*	-0.173	-0.089	-0.060	-0.252***	-0.166**	-0.116*	-0.018	-0.148***	-0.051
	(-1.68)	(-1.50)	(-0.76)	(-0.59)	(-3.19)	(-2.35)	(-1.95)	(-0.92)	(-2.89)	(-0.70)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA12: Reaction of earnings forecasts to ESG incidents—By novelty, reach and severity

This table reports the results of a regression of the changes in EPS forecasts on ESG incidents. In columns (1)-(7), the dependent variables are the changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variable is defined as 1 if any novel incidents happen in months $[t-6, t]$ and is 0 otherwise. In Panel B, the independent variable is defined as 1 if any high-reach incidents happen in months $[t-6, t]$ and is 0 otherwise. In Panel C, the independent variable is defined as 1 if any severe incidents happen in months $[t-6, t]$ and is 0 otherwise. Novel, high-reach and severe incidents are defined as those with RepRisk novelty, reach and severity measures that are equal to or larger than 2. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Novel incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 novel incidents in the past 6 months=1	-0.118*	-0.117	-0.087	-0.064	-0.096**	-0.137***	-0.150***	-0.016	-0.166***	-0.144***
	(-1.67)	(-1.59)	(-1.27)	(-1.11)	(-2.04)	(-3.21)	(-3.53)	(-1.37)	(-5.76)	(-3.86)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Reach incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 reach incidents in the past 6 months=1	-0.246***	-0.141*	-0.082	-0.091	-0.148***	-0.184***	-0.156***	-0.016	-0.166***	-0.151***
	(-3.26)	(-1.91)	(-1.22)	(-1.25)	(-3.11)	(-4.35)	(-3.90)	(-1.29)	(-5.73)	(-4.30)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Severe incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 severe incidents in the past 6 months=1	-0.174**	-0.185**	-0.197**	-0.221***	-0.195***	-0.178***	-0.143***	-0.006	-0.156***	-0.115**
	(-2.11)	(-2.28)	(-2.44)	(-3.07)	(-3.63)	(-3.54)	(-3.18)	(-0.46)	(-4.52)	(-2.49)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA13: Reaction of sales and margin forecasts to ESG incidents, balanced sample

This table reports the results of a regression of changes in sales and gross margin consensus forecasts on ESG incidents. In columns (1)-(7), the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon sales forecasts, defined by $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{F_{t-1} Sales_{t+h}} \times 100$. In columns (8)-(14), the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon gross margin forecasts, defined as $\frac{F_t GrossMargin_{t+h} - F_{t-1} GrossMargin_{t+h}}{F_{t-1} GrossMargin_{t+h}} \times 100$. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$ and is 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happens in months $[t-6, t]$, as 2 if more than 1 incident happens in months $[t-6, t]$, and as 0 otherwise. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
>=1 incidents in the past 6 months=1	-0.053**	-0.042*	-0.037*	-0.002	-0.018	-0.037**	-0.041**	-0.029	-0.024	0.006	0.017	-0.019	-0.017	0.002
	(-2.28)	(-1.92)	(-1.71)	(-0.09)	(-1.35)	(-2.58)	(-2.44)	(-1.60)	(-1.35)	(0.30)	(1.07)	(-1.64)	(-1.37)	(0.13)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.111	0.112	0.113	0.104	0.118	0.135	0.113	0.056	0.046	0.046	0.050	0.060	0.056	0.053
Obs.	130790	119149	104875	61208	296107	286165	181311	130790	119149	104875	61208	296107	286165	181311

Panel B: Splitting by the number of incidents

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
1 incident in the past 6 months	-0.039*	-0.031	-0.021	0.015	-0.011	-0.022	-0.020	-0.034*	-0.020	0.014	0.017	-0.022*	-0.016	0.010
	(-1.69)	(-1.34)	(-0.96)	(0.86)	(-0.81)	(-1.53)	(-1.17)	(-1.91)	(-1.10)	(0.72)	(1.05)	(-1.68)	(-1.17)	(0.66)
>=2 incidents in the past 6 months	-0.085***	-0.070**	-0.073**	-0.038*	-0.034*	-0.069***	-0.084***	-0.017	-0.035	-0.014	0.017	-0.012	-0.020	-0.015
	(-2.66)	(-2.32)	(-2.50)	(-1.69)	(-1.91)	(-3.56)	(-3.54)	(-0.65)	(-1.44)	(-0.58)	(0.74)	(-0.80)	(-1.26)	(-0.85)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.111	0.112	0.113	0.104	0.118	0.135	0.113	0.056	0.046	0.046	0.050	0.060	0.056	0.053
Obs.	130790	119149	104875	61208	296107	286165	181311	130790	119149	104875	61208	296107	286165	181311

Table IA14: Impact on sales forecasts of negative ESG incidents and other negative incidents

This table reports the results of a regression of the changes in consensus sales forecasts on ESG incidents and negative key development (KD) incidents. In columns (1)-(3), the dependent variables are changes in the 1-year, 2-year, and 3-year horizon sales forecasts, defined as $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{F_{t-1} Sales_{t+h}} \times 100$. The first independent variable takes on a value of one if at least one ESG incident happens in months $[t-6, t]$ and is zero otherwise. The second independent variable takes on a value of one if at least one negative KD incident happens in months $[t-6, t]$ and is zero otherwise. Column 4 and Column 5 report the corresponding regression results by pooling the 1- and 2-years and 1- and 3-year forecasts, respectively. The F-statistics and p-values are the results of the hypothesis test that $\beta_{ESG \times h} - \beta_{KD \times h} = 0$. Standard errors are double clustered at the firm and month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) 1 year	(2) 2 year	(3) 3 year	(4) 1&2 year	(5) 1&3 year
ESG Incidents in the past 6 months=1	-0.033***	-0.058***	-0.058***	-0.033***	-0.033***
	(-3.32)	(-4.84)	(-4.63)	(-3.33)	(-3.33)
KD Negative Incidents in the past 6 months=1	-0.061***	-0.066***	-0.043***	-0.061***	-0.061***
	(-6.74)	(-6.17)	(-3.33)	(-6.80)	(-6.80)
ESG Incidents in the past 6 months=1 × horizons=2				-0.025***	
				(-3.13)	
KD Negative Incidents in the past 6 months=1 × horizons=2				-0.005	
				(-0.72)	
ESG Incidents in the past 6 months=1 × horizons=3					-0.025**
					(-2.28)
KD Negative Incidents in the past 6 months=1 × horizons=3					0.018
					(1.52)
$\beta_{ESG \times h-year} - \beta_{KD \times h-year}$				-0.020	-0.043
F-stat				3.676	6.499
P value				0.057	0.012
Month × Industry × Country FE	YES	YES	YES	NO	NO
Firm FE	YES	YES	YES	NO	NO
Month × Industry × Country × Horizon FE	NO	NO	NO	YES	YES
Firm × Horizon FE	NO	NO	NO	YES	YES
adj R2	0.092	0.105	0.086	0.099	0.091
Obs.	552059	541902	417346	1093961	969405