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ESG news, future cash flows, and firm value

François Derrien
HEC Paris

Philipp Krueger
University of Geneva, Swiss Finance Institute, and ECGI

Augustin Landier
HEC Paris

Tianhao Yao
HEC Paris

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Francois Derrien†
Philipp Krüger‡
Augustin Landier§
Tianhao Yao ¶

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Abstract

We investigate how sell-side analysts adjust their earnings forecasts following negative ESG incidents. We find that after learning about negative ESG news, analysts significantly downgrade their earnings forecasts over all horizons, including long-term horizons. Negative ESG incidents affect earnings forecasts at longer horizons than other types of corporate incidents. The negative revisions of earnings forecasts reflect expectations of lower future sales (rather than higher future costs). Forecast revisions explain most of the negative impacts of ESG incidents on firm value. In Europe, analysts who exhibit greater sensitivity to ESG news provide significantly more precise forecasts than their peers.

JEL Classification: G32, M14

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†HEC Paris, Email address: derrien@hec.fr
‡University of Geneva, SFI, and ECGI, Email address: philipp.krueger@unige.ch
§HEC Paris, Email address: landier@hec.fr
¶HEC Paris, Email address: tianhao.yao@hec.edu

1 Introduction

The use of environmental, social, and governance (ESG) information has become a frequent theme in asset management. Bryan et al. (2020) identifies 534 sustainable index mutual funds and exchange-traded funds globally, with collective assets under management (AUM) of $250 billion. The money invested in these funds has more than doubled over the past three years. Launched in 2006, the UN-supported Principles for Responsible Investment (PRI) initiative has gathered more than 3,000 signatories, managing over $103 trillion in assets. Signatories of the PRI commit to "incorporate ESG issues into investment analysis and decision-making processes" and Gibson et al. (2021) find that more than half of all 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, the issue of the extent to which ESG information matters for firm value is still widely debated. In addition, the channels–if any–through which ESG news 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) and Bolton and Kacperczyk (2019).

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 that the firm produces high levels of pollution, shareholders might expect lower future earnings 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, long term, for instance, because customers or employees reject 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 presented, e.g., in Edmans (2011).

The main goal of our study is to investigate the *cash flow* channel: following ESG news, how do forecasted earnings change? Does it affect all horizons? Is it due do a change in forcasts of sales (growth) or margins? To investigate these questions, we combine a global sample of analyst earnings forecasts, sales, and margins over various horizons with ESG news data. Analyst forecast data serve as a proxy for expectations about future firm fundamentals. The ESG news data capture salient negative 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 news about negative ESG incidents. Using ESG news data rather than ESG ratings (or scores) allows us to avoid the well-documented inconsistency within ESG ratings. For instance, Berg et al. (2019) and Gibson-Brandon et al. (2021) document disagreement in the ESG scores issued by different data providers. In addition, Berg et al. (2020) document backfilling issues in the Refinitiv ESG data, a widely used ESG dataset. In addition to these methodological issues, another concern with using ESG scores is that these scores are typically slow-moving, and it is difficult to isolate why and when ESG scores change. 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. It proceeds as follows. Section 2 details the different data sets and variables used in our study. Section 3 describes our core results regarding whether and how analysts update their forecasts following ESG news. We provide evidence that negative ESG news shifts earnings forecasts over short *and* long horizons. The reaction is stronger when firms are subject to multiple 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 the implications of negative ESG incidents with those of other types of negative and value-relevant incidents, we find that negative ESG incidents have a longer-term impact on earnings forecasts than other events. Section 4 decomposes earnings forecast revisions into a component coming from sales revisions and a component coming from cost revisions. Our analysis suggests that the changes in analysts' earnings expectations are primarily driven by the anticipation of lower sales rather than of higher future costs. In Section 5, using a simple dividend discount approach, we show that changes in earnings forecasts can account for the negative response of firm valuations following ESG incidents. The implied change in the discount rate is not statistically significantly different from zero. Our finding is in line with that of Berk and van Binsbergen (2021), who show that ESG divestment has no detectable effect on the cost of capital of firms. It is also consistent with recent papers showing that a surprisingly 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. Section 6 studies the heterogeneity in our main result by geographic region, industry, and firm size. We find that our forecast revision effect is stronger for smaller firms and in B-to-C sectors (where advertising expenses are higher). In Section 7, we ask whether analysts who are more sensitive to ESG news issue forecasts that are more or less precise than those issued by their peers. We find that overall, ESG-sensitive analysts issue more precise forecasts, but the difference is statistically significant only in Europe. Section 8 concludes.

Literature Review. According to a widely cited meta-study (see Friede et al. (2015)), the majority of prior research has documented a nonnegative association between firm ESG policies and measures of financial performance. However, the exact mechanisms through which ESG policies translate into financial performance or firm value remain ambiguous, and it is often hard to establish the direction of causation (Hong et al. (2012)). A recent working paper has also highlighted the issue of measurement error (see Berg et al. (2021)).

While prior research has documented mostly correlational evidence, some papers have attempted to identify specific mechanisms through which ESG policies might affect cash flows or discount rates. For instance, Servaes and Tamayo (2013) stress that a firm's ESG policies can affect consumer behavior, thereby enhancing cash flows and firm value. 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. Other papers have focused on the effect of ESG policies on the cost of capital and provide evidence that better ESG policies are associated with a lower cost of capital (e.g., Chava (2014), Dunn et al. (2018), Albuquerque et al. (2019)). Overall, however, the extent to which asset prices incorporate or do not incorporate sustainability, and whether this is through a cash flow and/or cost of capital channel is still relatively poorly understood. Our paper sheds light on this issue by focusing on the effects of material ESG-related news.

Other papers in the finance literature have examined a variety of ESG-related topics. For instance, Lins et al. (2017) study whether stock markets valued better ESG policies during the Great Financial Crisis. Using the introduction of the Morningstar ESG fund rating, Hartzmark and Sussman (2018) examine whether investors care about a mutual fund's ESG characteristics. Liang and Renneboog (2017) explore the determinants of corporate social responsibility policies and highlight the important role of the legal origins of the country in which a firm is headquartered. Ferrell et al. (2016) empirically study how sustainability relates to agency issues and find a positive correlation between ESG scores and firm value. Other researchers have used experimental methods to shed light on why investors hold socially responsible mutual funds (see Riedl and Smeets (2017)), whether individuals are willing to use their pension savings to promote sustainability (Bauer et al. (2019)), or whether shareholders value ethical firm actions (see Bonnefon et al. (2019)). Given the dearth of finance theory on how to think about ESG investing, a host of theory papers concerned with sustainability and ESG have recently emerged. For example, Pastor et al. (2019) develop a theoretical model to study the financial and real effects of sustainable investing. Pedersen et al. (2019) develop a theory of the potential costs and benefits of ESG-based investing and derive an ESG-efficient frontier. Oehmke and Opp (2019) develop a theory of socially responsible investment, and Landier and Lovo (2020) study whether and how sustainable finance can have a real impact on the reduction of negative externalities. Some other research has also examined RepRisk data. Akey et al. (2021) shows that reputation-related Reprisk incidents negatively affect firm value. Related to our work are two concurrent working papers that also use RepRisk data but with different focuses. Gantchev et al. (2021) 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. Using a different angle from these papers, we focus on how ESG incidents affect forecasts of future cash-flows, sales and margins at various horizons.

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.

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 relation exists between ESG events and subsequent changes in 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 analyst 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[2].

[2] 100% of consensus PTGs are for 12 months ahead. We dropped 10.5% of the individual-level PTGs for other horizons.

We use both the monthly consensus forecasts and the detailed individual-level forecasts from IBES. We use the monthly consensus forecast (summarized by IBES every month on the Thursday before the third Friday) for the month-level analysis. We use detailed individual-level forecasts to construct daily consensus forecasts used in the event studies. Specifically, we forward fill the individual-level forecasts to calendar days to define daily-level individual forecasts. We take the median of all daily individual forecasts to define our daily consensus forecasts after dropping those forecasts older than 365 days and those observations with fewer than 2 analyst forecasts.

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 the IBES data using the last trading day before the IBES consensus forecast date. For US companies, we match the CRSP/Compustat data with the IBES data using CUSIP numbers. For international companies, we match the Compustat data with the IBES data using SEDOLs. We merge the Compustat data with the IBES data 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 forecast 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.[3] 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.

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

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.[4] 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 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

3.1 Event study

In this section, we start our analysis by examining whether and how ESG-related news induces changes in analyst forecasts and then analyze the determinants of these changes. We examine whether analysts react to incidents by changing their earnings forecasts and whether they change their forecasts differentially for different horizons. For this investigation, we use daily analyst forecasts and conduct an event study. A

[4]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.

firm with an incident on date d_t is considered to be a "treated" firm, which in our context means that the firm has experienced at least one ESG incident. Each treated firm is matched to a control firm, i.e., a firm in the same industry and country as the treated firm but with no ESG incident during $[d_{t-30}, d_t]$. Among all potential control firms, we choose the firm that is the closest to the treated firm in terms of market capitalization one day before the ESG news day d_t. Because in a given month, firms can be subject to multiple ESG incidents, in order to avoid overestimating the impact of each incident, we focus on observations with no other incident in the previous 30 days. To further control for possible pretrend and valuation differences between the treated and control firms, for each day s around the ESG incident, we run the following regression:

$$\Delta F_{d_{t+s}} EPS_{i,d_t+h} = \alpha_s + \beta_s \Delta(F_{d_t-1} EPS_{i,d_t+h} - F_{d_t-180} EPS_{i,d_t+h}) + \gamma_s \Delta(B/M)_{i,d_t-1} + \epsilon_{i,d_t} \tag{1}$$

where the dependent variable is the difference between the change in the scaled forecasts of the treated and control firms over the same horizon on date d_{t+s} (see Section 2.4 for details on the definition of forecast changes).[5] $\Delta(F_{d_t-1} EPS_{i,d_t+h} - F_{d_t-180} EPS_{i,d_t+h})$ is the difference in the EPS change between the treated and control firms 180 days before the ESG incident. This term is included to control for the pretrend in EPS forecast changes. $\Delta(B/M)_{i,d_t-1}$ is the difference in the book-to-market ratio between treated and control firms one day before the occurrence of the ESG incident and is used to control for the market valuation of the firms before

[5] We scale the EPS forecasts using the EPS forecasts from one day before the ESG incidents, i.e., d_{t-1}.

the ESG incident occurs. The coefficient estimate of interest is α_s, which measures the difference in the forecast changes between the treated and control firms s days relative to the incident (i.e. before or after). To accumulate the impact after the ESG incidents, we require the incidents to happen at leaat 180 days before the earnings announcement dates. We estimate similar regressions for $PTGs$, raw returns, and the FF3-alpha. The regression that uses FF3-alpha as the dependent variable is estimated only for the US sample, and the risk adjustment is carried out using the Fama and French (1993) three-factor model. We double cluster the standard errors at the firm and month level to account for possible dependence across firms and months.

Figure 3 about here.

We plot the coefficient estimates α_s—which measure the differences in the EPS forecast changes between the treated and control firms—as a function of s, the number of days relative to the day on which the ESG incident occurred. As shown in Figure 3, before day 0, that is, the day of the ESG incident, the average changes in earnings forecasts (see Panel (a)) or in PTGs (see Panel (b)) are not different between the two groups of firms. After day 0, however, analyst forecast revisions for the two groups of firms start diverging. This divergence is gradual, indicating that the analysts' reaction takes time to materialize, and it is roughly of similar magnitude for all horizons (1-3 years). Panel (b) plots the relative evolution of PTGs and returns for the treated and control firms. In line with Panel (a) and the fact that ESG events have an impact on expected profits, firms subject to negative ESG events have returns that are on average approximately 2 percentage points lower than those of their matched firms one year after the event. This effect is not driven by common factors, as it is of the same magnitude when we replace the raw returns with returns adjusted with the three-factor model. The evolution of PTGs shows a similar pattern, mimicking the evolution of the raw and adjusted returns. Thus, analysts' predictions following ESG events appear to be approximately in line with those of investors.

3.2 Panel regression analysis

We now explore the patterns documented in the previous section in a regression setting. The regression analysis allows us to estimate the term structure of how analysts change their forecasts following incidents. The objective is to better understand whether analysts believe that ESG incidents have only a short-term effect on profits or instead reflect issues that will materialize mostly over longer horizons. 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:

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

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 underreaction in analysts' forecast revisions[6]. 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[7]. 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 these 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 percentage points) is roughly equal to that for the two- or three-year horizons (-0.143 and -0.150 percentage points, respectively). We conclude that following ESG incidents, there is an almost parallel shift in analysts' EPS forecasts. This is confirmed in Column 8, in which the effect of ESG incidents

[6] 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 IA4.

[7] The results discussed below 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 IA5, IA6, and IA7.

on the forecasted 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. In line with the finding in Figure 3, the two effects are significantly negative and of similar magnitudes.

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 percentage points across all forecast horizons for firms with one incident in the past six months, while they vary between -0.125 and -0.302 percentage points 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, see changes in the EPS forecasts of analysts that are roughly constant across all horizons.

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 2 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 IA8 reports the detailed estimates of the impact of these negative events across different forecast horizons. To better compare the term structure, we normalize the impact of the event over different horizons by its impact over the one-year horizon. As shown in Figure 4, the impacts of ESG incidents are persistent across horizons. On average, the impact of an ESG incident on earnings forecasts over the three-year horizon is 1.36 times as large as its impact on one-year earnings forecasts. In 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 only 55% 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:

$$\begin{aligned}\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1}EPS_{i,t+h})} = \alpha &+ \beta\, \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \\ &+ \eta\, \mathbb{1}\{KD\ Negative\ Events\ in\ [t-6,t]\} \\ &+ \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}\end{aligned} \tag{3}$$

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. Based on the evidence above, we conclude that ESG incidents have a longer-lived impact on earnings forecasts than other types of negative incidents. The next section tries to disentangle different economic explanations of this fact.

Figure 4 about here.

Table 3 about here.

Appendix Table IA9 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 the fact that the E incidents reported by RepRisk are not as serious as incidents in the two other categories. In Appendix Table IA10, 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 IA11 reports the results of a regression in which we consider only those 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.

4 Economic mechanism: Sales vs. costs

Why do analysts anticipate such long-term 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. ESG news shrink the customer base of the firm, which translates into lower long-term sales. Second, it is likely that firms cannot quickly adjust their productive technology to "repair" their ESG issues. Future earnings could hence decrease (even if sales are stable) if 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 earnings to be affected by negative ESG incidents, we estimate two sets of regression equations similar to Equation 2, 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 reports the results of these regressions, which suggest that the anticipated decrease in earnings documented earlier is expected to happen through a reduction in sales. The coefficients on the ESG incident dummy variable are consistently negative in columns (1)-(7) of Panel A and statistically significant over most horizons. 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. Overall, these results suggest that analysts expect negative ESG incidents to affect future earnings mostly through reductions in sales.

Table 4 about here.

To compare the impact on expected sales of ESG incidents and other Key Development incidents, in Appendix Table IA12, we report the results of regressions similar to Equation 3, 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 compare 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 reasons why stock values might 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 that leaves the formula's hypothesis of constant growth unchanged is:

$$\frac{\Delta PV_{it}}{PV_{it}} = \frac{\Delta F_t EPS_{i,t+1}}{F_t EPS_{i,t+1}} - \frac{\Delta r_{it} - \Delta g}{r_{it} - g} \tag{4}$$

However, 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) to the coefficients in columns (5)-(7) translates to $\frac{\Delta PV_{it}}{PV_{it}} \simeq \frac{\Delta F_t EPS_{i,t+1}}{F_t EPS_{i,t+1}}$.

Hence, going back to Equation 4, the coefficients observed in Table 3 suggest that

$$\Delta r_{it} = 0,$$

which means that we cannot reject that there is no change in the discount rate and that changes in expected future earnings explain all 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 payouts 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 as of 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 ratios 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 as of time t, and g_t is the expectation for long-run nominal GDP growth given by macro forecasters. We do not use forecasts beyond year 3 because they are most 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:

$$PV_{it}(r_{it}) = P_{it} \tag{5}$$

where P_{it} is the stock price of firm i at time t. We keep only those 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 2, replacing 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 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. In other words, using the simple valuation formula above, changes in earnings forecasts alone predict 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 of our decomposition.

6 Heterogeneity

In this section, we ask whether the effects documented above 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, the skill of analysts, 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 is due to consumer preferences in some regions but not others. To test this hypothesis, we use firms located in North America (the US and Canada) as the baseline sample and further interact the ESG incident variables with dummies indicating $EU15$, $Asia$ and $Others$, where $EU15$ indicates the 15 most developed countries in Europe as defined by the United Nations[8] and $Others$ mostly includes firms in South America, Australia, and Africa. We focus on annual forecast data, as quarterly forecasts are predominantly available only for US firms.

Table 6 about here.

Panel A of Table 6 reports the effects of ESG incidents on EPS, PTGs, and returns

[8]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`

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 reacts less to ESG incidents than in other geographic areas. There is not much difference in terms of the reaction 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. For example, firms in the energy industry are more likely to have an ESG incident in an average month than firms in the consumer services industry. The average number of incidents by industry is shown in Figure 5. 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 5 about here.

Figure 6 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 7 is very similar to the ranking presented in Figure 6.

Figure 6 about here.

Figure 7 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 4 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 8 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 2, 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 8 about here.

Table 7 about here.

6.3 Large vs. small firms

Finally, we 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 9 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 more ESG incidents per month than firms in the first decile. Therefore, ESG news could 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 become 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 for 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 9 about here.

Table 8 about here.

7 Are ESG-sensitive analysts better or worse forecasters?

In the last section of this paper, we explore whether specific analyst characteristics are associated with a greater sensitivity to ESG incidents. To do so, 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. 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 (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 45 days after an announcement of total 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. 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 those firm-level characteristics that are related to forecast precision.

Table 9 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 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. 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 because ESG news has a greater impact on the operating performance of European firms.

Table 9 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 long 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 can be explained by changes in earnings forecasts. We show, through a simple discounting exercise, that the discount rate implied by the valuations does not change from before to after negative ESG news 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 strategy 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., 2020), 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., 2019). 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 10 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 10 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.

Table 10 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.

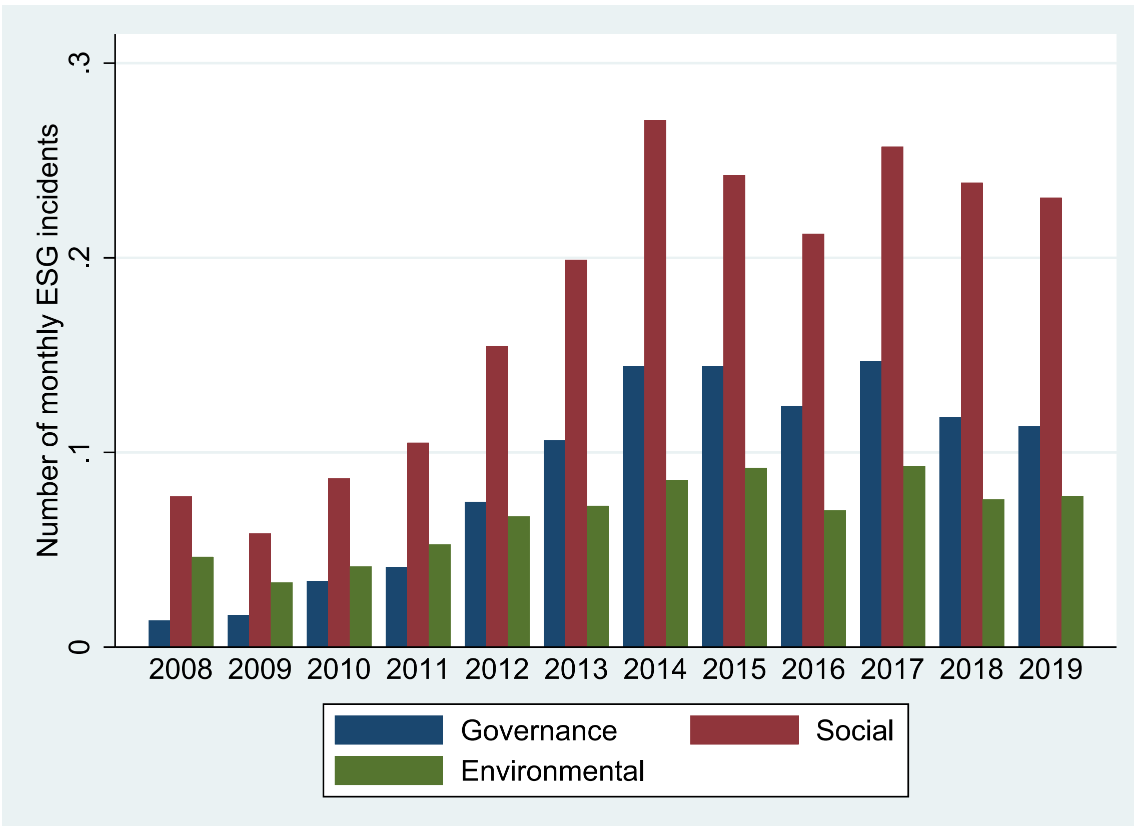


Figure 2: Timing of ESG incidents and analyst forecasts

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.

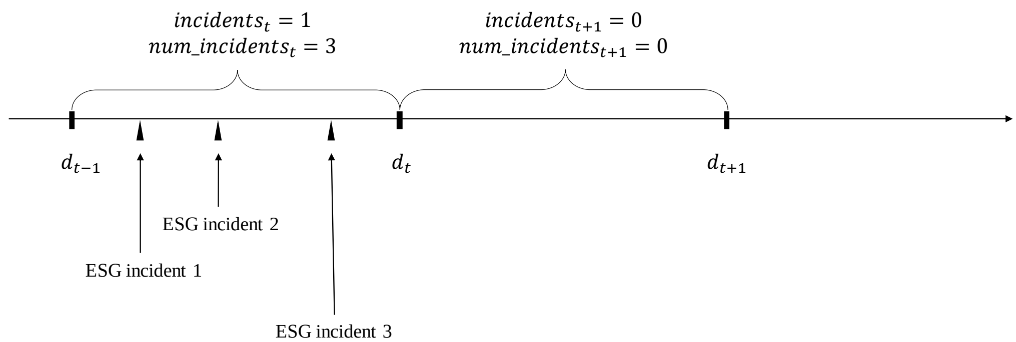
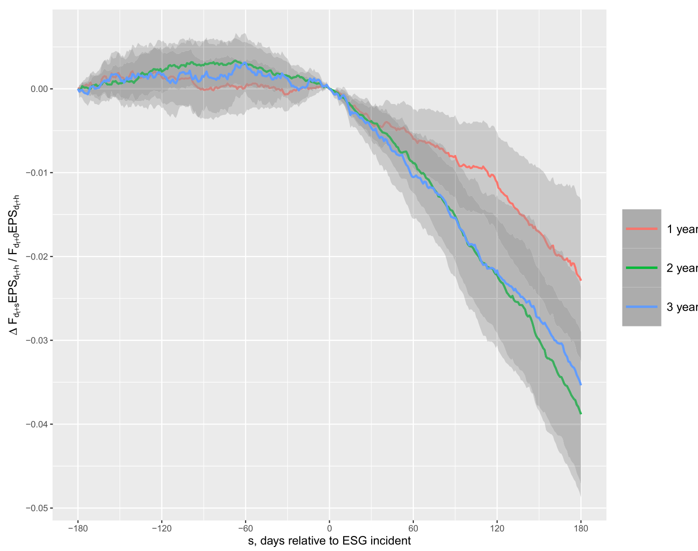


Figure 3: Daily EPS/PTG forecast changes after incidents

This figure reports the results of an event study using ESG incident shocks. The horizontal axis is the number of calendar days relative to the ESG incidents. The vertical axis is the evolution of the difference in EPS forecasts, PTGs, and returns between (treated) firms that have ESG incidents on day 0 and control firms. Specifically, for each ESG incident for each treated firm, the chosen control firm is a firm without any ESG incidents within the 30 days before day 0, that belongs to the same industry-country pair and that is the closest in size to the treated firm. The y-axis is defined as the difference in the EPS forecasts, PTGs, and returns after controlling for the firm's value factor and trends before the ESG incident. Specifically, for each day s relative to the incident day, the difference is defined as the intercept α_s from the equation $\Delta Y_{i,d_t+s} = \alpha_s + \beta_s \Delta(Y_{i,d_t-1} - Y_{i,d_t-180}) + \gamma_s \Delta B/M_{i,d_t-1} + \epsilon_{i,d_t}$, where Y is the EPS or PTG forecast or the return. We restrict the ESG incidents to those incidents for which the treated firm has no other incidents within the 30 days before day 0. Figure (a) shows the change in the 1-year, 2-year, and 3-year horizon EPS forecasts. Figure (b) shows the changes in the PTG forecasts, the raw returns, and the excess returns from the Fama–French 3-factor model (excess returns are restricted to the US sample). Shaded areas are the 95% confidence intervals of corresponding estimates. Standard errors are double clustered at the firm and month level.

(a) EPS forecasts



(b) PTGs and returns

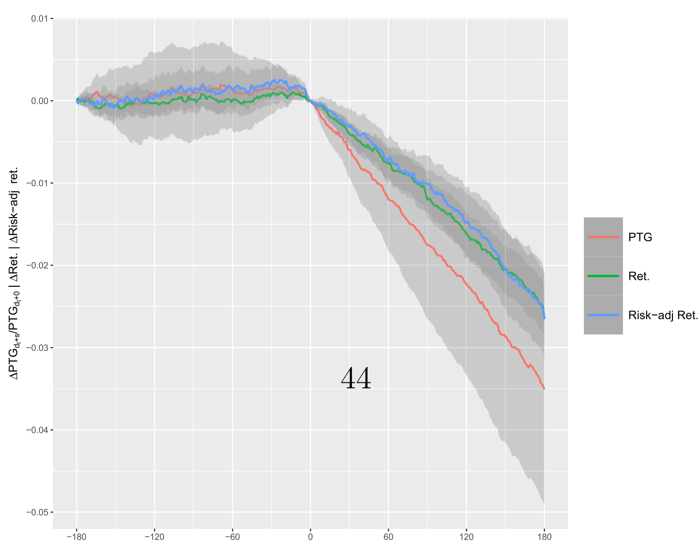


Figure 4: Term structure of the impact on earnings forecasts

This figure reports the term structure of different types of negative events. For each event type u and horizon h, we estimate the regression equation $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1}EPS_{i,t+h})} = \alpha + \beta\, \mathbb{1}\{type\ u\ incidents\ in\ [t-6,t]\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$, 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 IA8. 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 Kkey Development events. The bold red line represents the term structure of the ESG incidents.

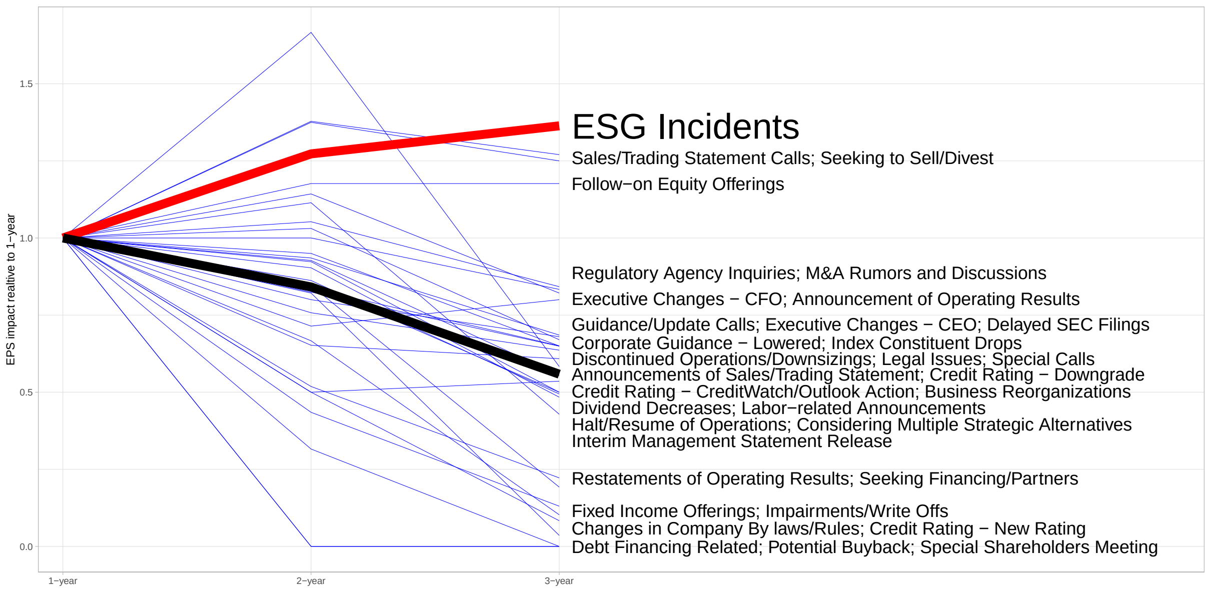


Figure 5: Number of incidents by industry

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

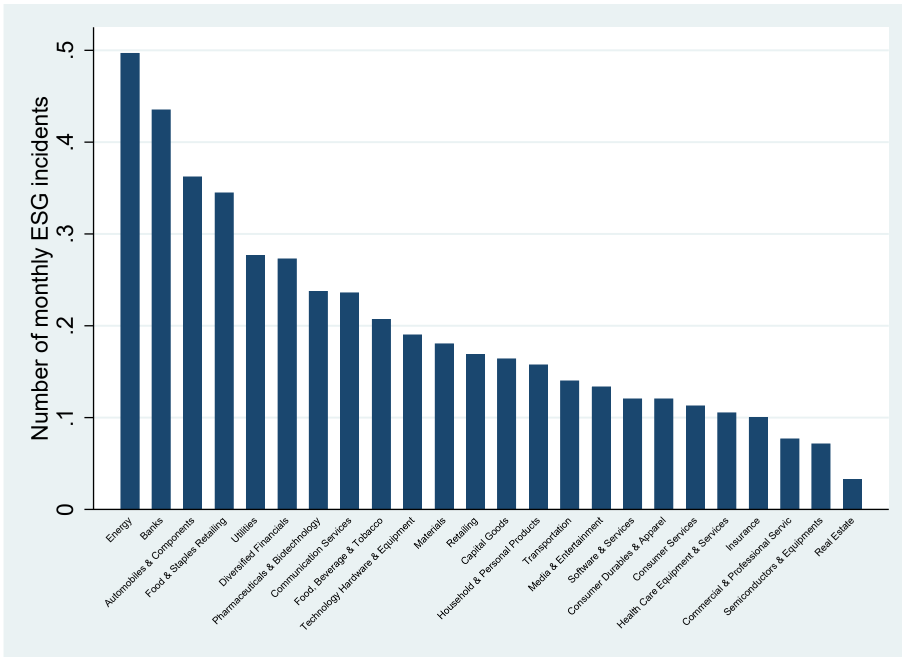


Figure 6: EPS sensitivity by industry

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., $(\beta_j^1 + \beta_j^2 + \beta_j^3)/3$.

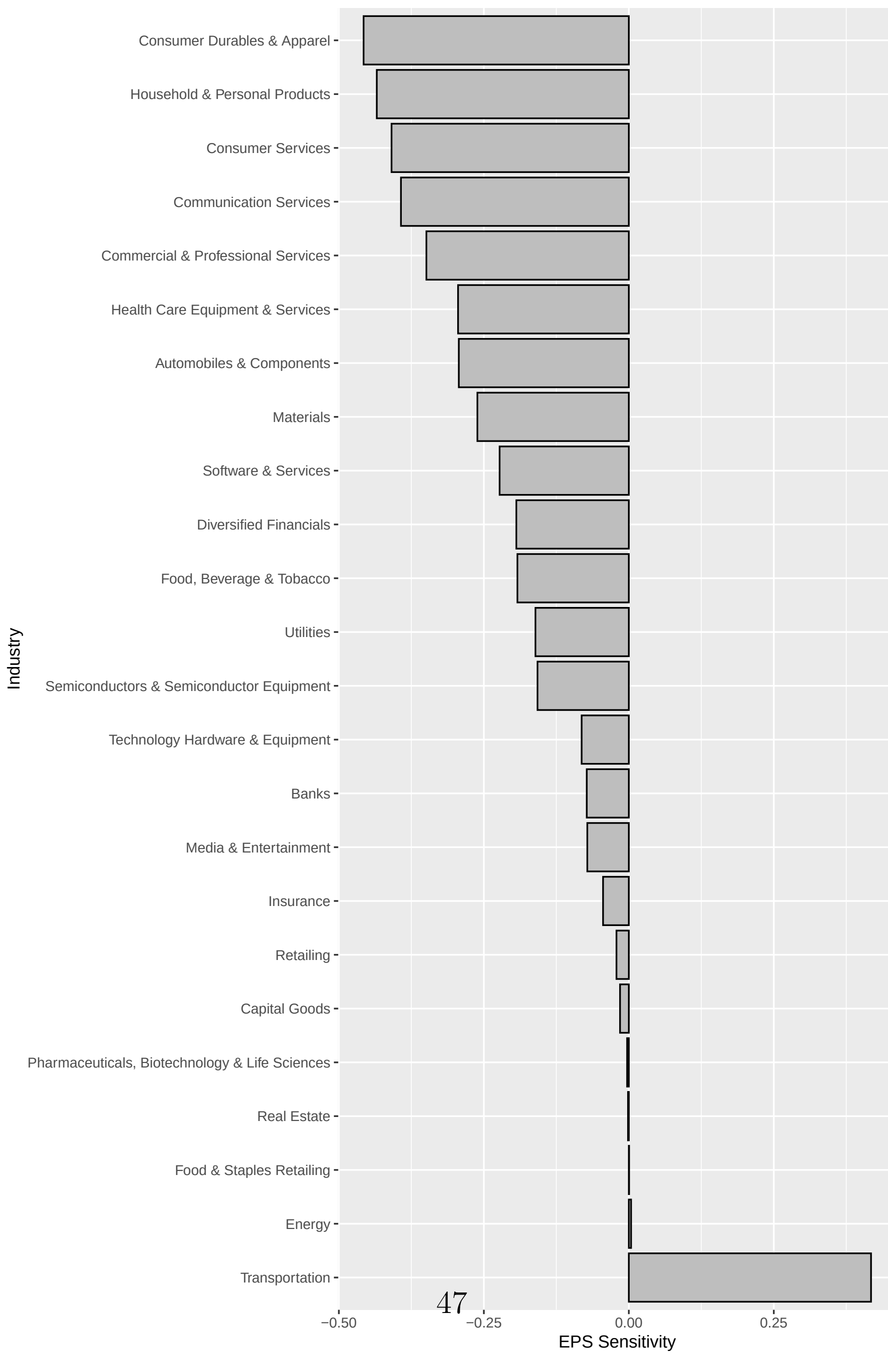


Figure 7: PTG sensitivity by industry

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.

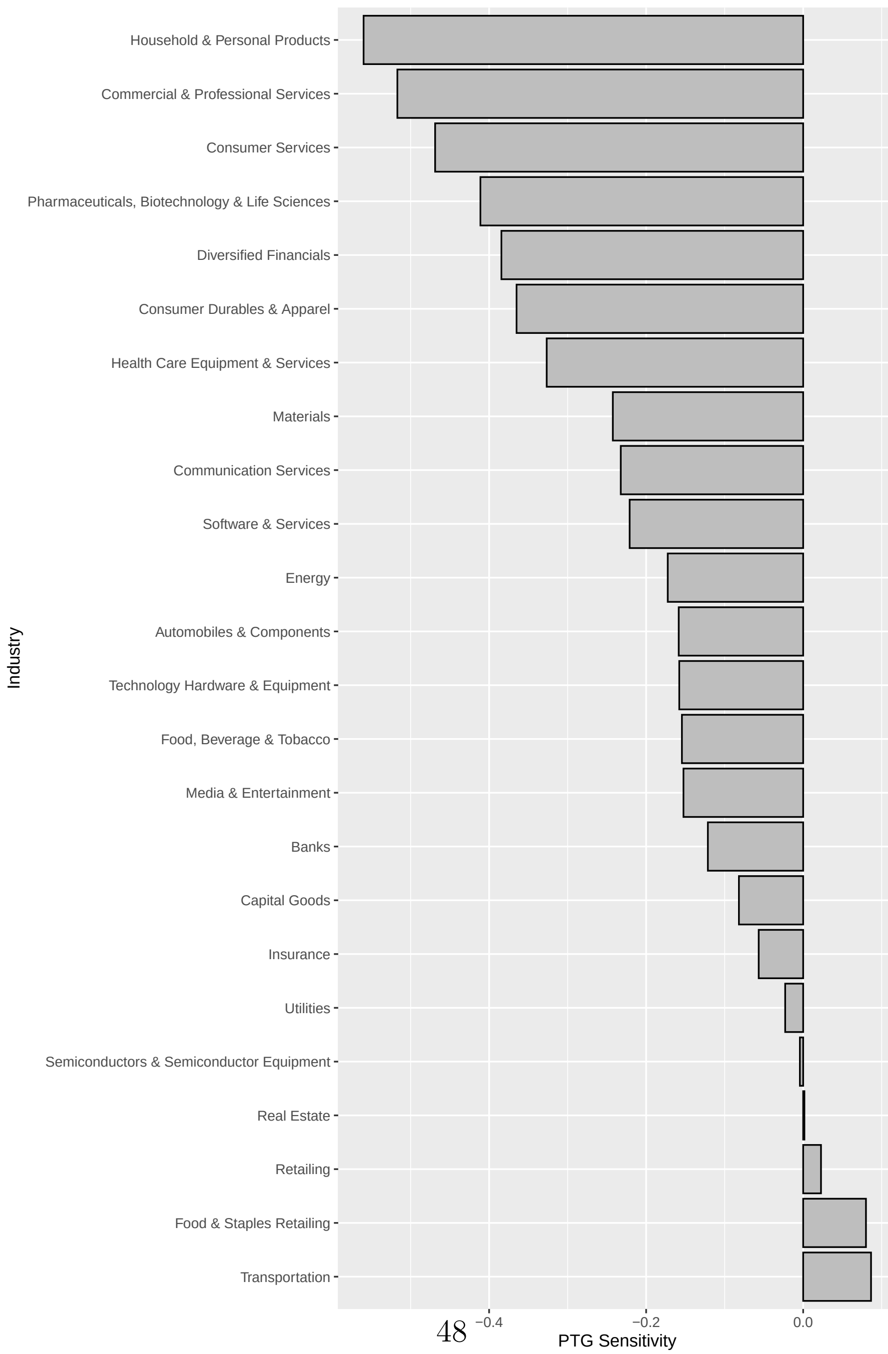
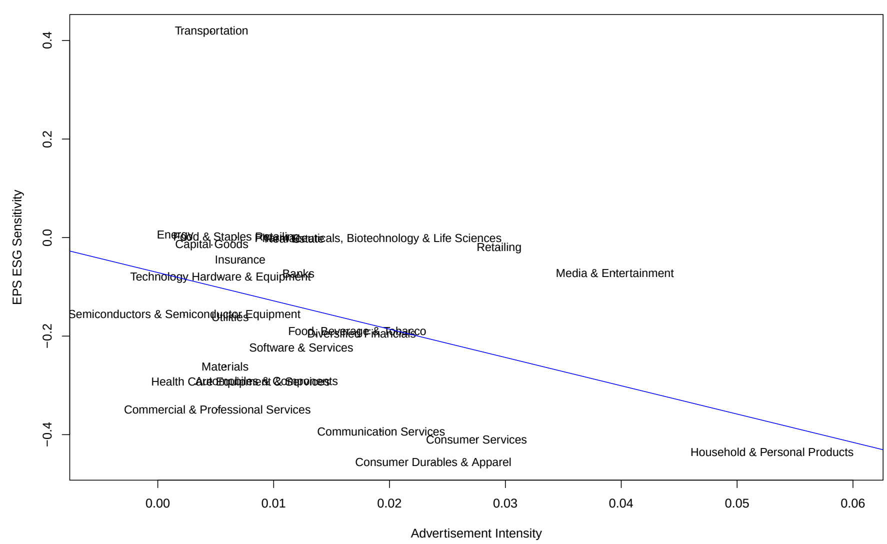


Figure 8: EPS/PTG sensitivity and advertising intensity

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

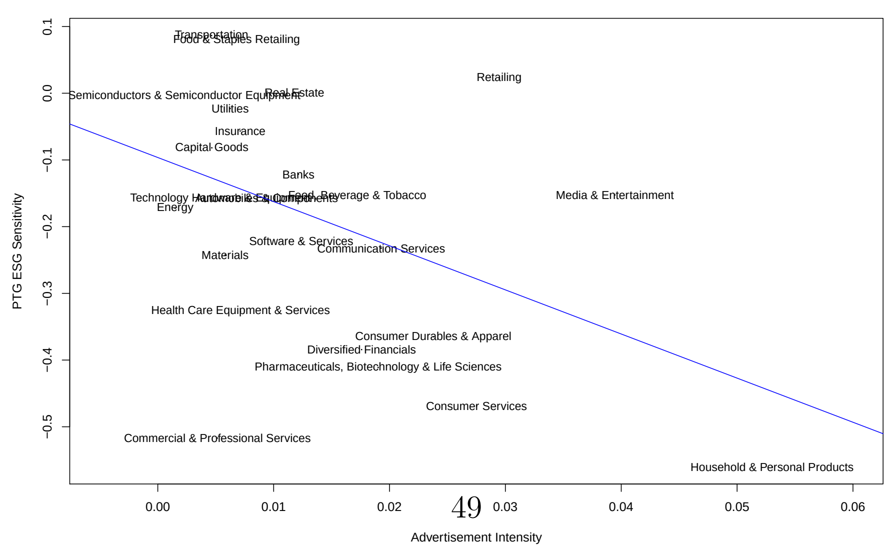
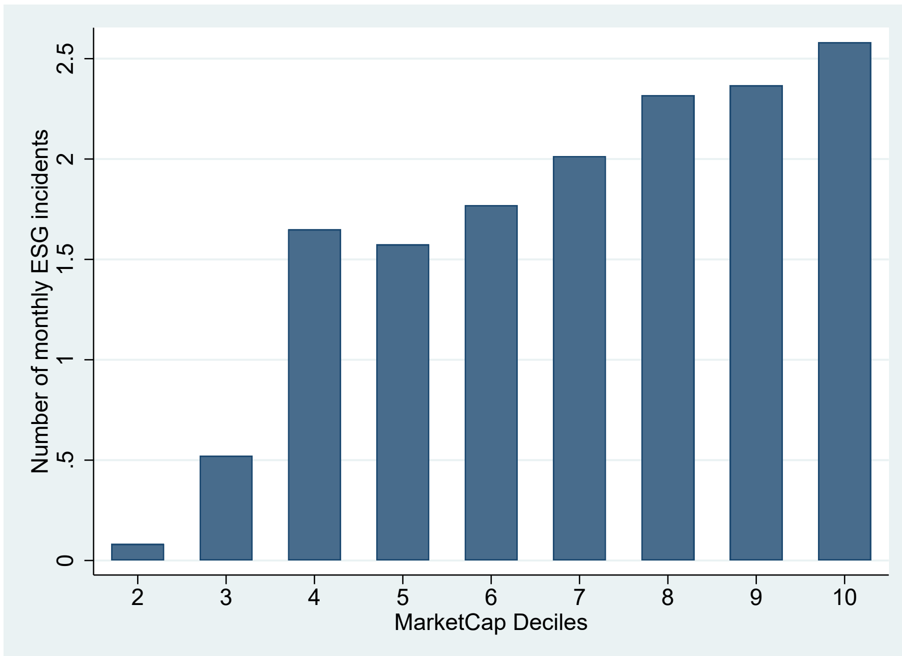


Figure 9: Number of incidents by size

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 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: 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 on EPS forecasts of negative ESG incidents and other negative incidents

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)
$\beta_{ESG\times h\text{-}year} - \beta_{KD\times h\text{-}year}$				-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) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) Q1	(9) Q2	(10) Q3	(11) Q4	(12) 1 year	(13) 2 year	(14) 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: Number of incidents

	Sales							GrossMargin						
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) Q1	(9) Q2	(10) Q3	(11) Q4	(12) 1 year	(13) 2 year	(14) 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 percentage points) in month t, defined in Section 5.2. In Column (4), the dependent variable is the cumulative return (in percentage points) 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	-0.188**	-0.108*	-0.169***
	(-0.10)	(-0.38)	(-2.33)	(-1.72)	(-3.53)
Month × Industry FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
adj R2	0.355	0.373	0.038	0.314	0.154
Obs.	164943	164943	164943	209587	192120

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

	(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

	(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

	(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: 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 10: 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 tables 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: 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	LTG	PTG	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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	LTG	PTG	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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	LTG	PTG	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 IA5: 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: 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 IA6: 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: 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 IA7: 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: 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 IA8: Impact on earnings forecasts by type of negative event

scriptsizeThis 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 percentage points.

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 IA9: 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 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 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 $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, 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 IA11: 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 IA12: 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)	(2)	(3)	(4)	(5)
	1 year	2 year	3 year	1&2 year	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

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c/o University of Geneva, Bd. Du Pont d'Arve 42, CH-1211 Geneva 4
T +41 22 379 84 71, rps@sfi.ch, www.sfi.ch