ESG news, future cash flows, and firm value*

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Abstract

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

JEL Classification: G32, M14

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1 Introduction

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

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

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

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

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

To investigate these questions, we combine a global sample of analyst forecasts of earnings, sales, and margins over various horizons with negative ESG news data. Analyst forecast data serve as a proxy for expectations about future firm fundamentals. The negative ESG news data capture salient point-in-time shocks to analysts' beliefs about the ESG characteristics of firms. Our approach is to explore whether and how analysts change their earnings forecasts as a result of learning about these negative ESG incidents.

We use ESG news data rather than ESG ratings (or scores) for multiple reasons. Firstly, this allows us to avoid the well-documented inconsistency of ESG ratings. For instance, Berg et al. (2022) and Gibson-Brandon et al. (2021) document disagreement in the ESG ratings issued by different data providers. In addition, Berg et al. (2021) document backfilling issues in the Refinitiv ESG data, a widely used ESG dataset. Besides these methodological issues, another concern with using ESG ratings is that these ratings tend to move slowly and for reasons that are not always clear. They can change, for example, following a periodic (e.g., annual) rating revision by the rating provider, the release of new ESG information by firms through ESG/sustainability reports, ratings changes at peer firms, changes in rating methodologies, etc. Berg et al. (2023) find that ESG fund ownership reacts to changes in MSCI ESG ratings, but the reaction is slow—over a period of up to two years, which suggests that the reaction comes from compliance instead of information about fundamentals. In contrast, ESG news events provide cleanly identifiable shocks to a firm's ESG characteristics and fundamentals, which are more suitable to study analyst forecasts revisions.

Our analysis delivers several novel stylized facts. Exploiting the rich term structure of earnings forecasts, we provide evidence that negative ESG news shifts earnings forecasts over both short *and* longer horizons. The reaction is stronger when firms are subject to multiple negative ESG news incidents and when the news is related to social issues. We also find that the implications of negative ESG news for future earnings are not redundant with those of other proxies for firm quality (e.g., profitability) available at the time the news becomes available, suggesting that ESG news is not captured by existing accounting information.

Moreover, when contrasting earnings forecast revisions following negative ESG incidents with analyst reactions to other types of negative events (e.g., executive changes, reorganizations), we find that negative ESG incidents have a longer-term impact on earnings forecasts than other events. Specifically, we establish that the analyst reaction to negative ESG news is approximately constant across horizons, whereas other types of negative events result in a more pronounced negative reaction in the short-term. Another way of interpreting this finding is that while negative ESG news events appear to result in a permanent shift in EPS earnings forecasts (i.e., roughly constant over horizons), analyst reactions with respect to other types of negative corporate news events appear more transitory (i.e., stronger at short horizons (1-year), and weaker for longer horizons (3-years)).

We also provide evidence of considerable heterogeneity in our main result by geographic region, industry, and firm size. For instance, we find that our ESG forecast revision effect is stronger for smaller firms.

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

As explained above, ESG might affect firm value through a cash flow or a discount rate channel. While the main objective of our paper is to shed light on the importance of the cash flow channel, we also evaluate the relative importance of both channels in driving stock market values following negative ESG events. Using a simple dividend discount approach, we decompose negative ESG news induced changes in firm value in a component coming from changes in cash flow expectations and a component resulting from changes in discount rates. Our analysis shows that changes in earnings forecasts can account for most of the negative response of firm valuations following ESG incidents, while we do not find significant changes in implied discount rates. This is in line with the conclusions of Berk and van Binsbergen (2022), who argue theoretically that ESG divestment has no detectable effect on the cost of capital of firms. Empirically, Lindsey et al. (2021) show that ESG scores do not convey novel information about systematic risk beyond what is already known from other firm characteristics (e.g., quality, volatility, etc.). Our findings are also consistent with recent papers showing that a large fraction of medium-term stock price movements can be attributed to changes in earnings expectations (Engelberg et al. (2018); Lochstoer and Tetlock (2020); De-La-O and Myers (2021)) rather than changes in discount rates. One caveat of our discount rate analysis is that the tests may lack statistical power. Therefore we cannot rule out the possibility that the discount rate channel is also at play. Overall, our evidence suggests that, quantitatively, the decline in firm value following negative ESG news results from changes in expected cash flows.

In the final part of the paper, we examine whether analysts are correct in downward adjusting earnings and sales forecasts. We first test whether realized earnings and sales decrease following negative ESG news. We find that both realized earnings and sales drop after ESG incidents, which suggests that analysts are right to downward adjust their earnings forecasts following such incidents. Secondly, we exploit the rich IBES analyst-by-analyst forecast data and compare analysts who downward adjust EPS forecasts following negative ESG news to those analysts who do not. We confirm that forecast errors decrease for analysts who downward adjust EPS forecasts following ESG incidents, compared to analysts who do not downward adjust EPS forecasts in the same month, for the same firm and forecast horizon. Overall, these findings suggest that the recognition of ESG concerns is rational rather than a "fad".

Literature Review. The question of whether and how ESG issues contribute to financial performance is still widely debated, both among practitioners and academics. For instance, Hong and Kacperczyk (2009) and Bolton and Kacperczyk (2021) present evidence of out-performance by stocks with low ESG performance. Bolton and Kacperczyk (2021) document a link between stock returns and carbon emissions while Aswani et al. (2024) highlight that this relation might not hold universally, but depends on whether using scaled or unscaled emissions and focusing on reported versus vendor-estimated emissions.. Other papers present evidence of out-performance of high ESG stocks (e.g., Kempf and Osthoff (2007), Edmans (2011)). Focusing on measures of valuation, some researchers have documented a positive correlation between ESG scores and firm value (e.g., Ferrell et al. (2016)). Other papers in the literature have attempted to identify specific mechanisms through which ESG policies might affect cash flows and valuation. For instance, Servaes and Tamayo (2013) demonstrate that companies' ESG policies influence consumer behavior, which can impact future cash flows and the valuation of companies whose customer base consists mostly of individual customers. In a similar spirit, Krueger et al. (2023) focus on another key stakeholder (i.e., workers) and provide evidence that firms with better ESG policies pay lower wages. They conclude that ESG policies can generate higher value for shareholders through a reduction in labor costs.

Another stream of the literature focuses on the cost of capital by examining the effect of ESG policies on measures of (systematic) risk. Dunn et al. (2018) and Albuquerque et al. (2019), for instance, provide evidence that better ESG policies are associated with lower systematic risk. More recently, Lindsey et al. (2021) construct a rich dataset using ESG scores from seven major ESG data providers and combine these ESG scores with a large set of other stock characteristics (see Jensen et al.

(2022)). Contrary to some prior studies, they conclude that when controlling for a substantial amount of the conditioning information investors have at their disposal, ESG measures do not convey novel information about systematic risk.

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

2 Data

2.1 RepRisk and other ESG scores

Our main ESG data come from RepRisk. RepRisk produces daily indicators for negative ESG-related incidents at the firm level. It does so through a daily analysis of a large set of documents in 20 languages obtained from public sources. The data go back to January 2007, with daily granularity. RepRisk classifies ESG incidents according to 28 distinct issues. Environmental issues include news about climate change, pollution, waste issues, etc. Social issues relate to child labor, human rights abuses, etc. Governance issues capture issues such as executive compensation, corruption, etc. Panel A of Table 1 shows the full list of issues and Panel B shows the distribution of environment, social, and governance incidents. Approximately half of the incidents are associated with two or more E/S/G categories (Panel B). Events related to social issues are the most frequent in the RepRisk data. Figure 1 shows the average number of monthly incidents per firm by year. The number of ESG incidents recorded by RepRisk has increased with time. 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. Panel C of Table 1 shows the distribution of novelty, reach, and severity levels. No incidents are labeled as novelty-3 incidents and only 1% of incidents are labeled as severity-3 incidents. Appendix Table IA.1 gives a list illustrative examples of RepRisk incidents. For instance, Microsoft was criticized for sourcing cobalt from the Democratic Republic of Congo, which involved child labor and human right abuses issues. JinkoSolar, a Chinese solar company, was accused of water pollution, which led to protests by local residents.

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

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

RepRisk prides itself with supplying distinct data compared to traditional ESG ratings, as Reprisk data are primarily news based. The news captures the impacts that firms have on the the environment (e.g., greenhouse gas emissions, toxic releases), workers (e.g., workplace accidents), or communities (e.g., tax evasion). As RepRisk incidents are observable outcomes of firms' ESG policies, they reflect (at least partially) the ESG processes of firms.[1] As such, they are signals about the quality of firm's ESG practices and, more generally, about their ESG policies.

To confirm that RepRisk incidents provide information about firms' ESG practices, we explore the relation between RepRisk incidents and the ESG scores used in the existing ESG literature. We use ESG scores from Refinitiv (previously Asset4),[2] Morningstar Sustainalytics (hereafter Sustainalytics), and MSCI. We create a monthly panel using the three scores. We adjust all the scores to a 0-100 scale to make them comparable. We match RepRisk with these datasets through international securities identification numbers (ISINs). In Appendix A, we show that a strong and significantly negative relation exists between ESG events and subsequent ESG ratings. The latter finding justifies our use of ESG incidents as negative shocks to the ESG profiles of firms.

[1]For a discussion of how the metrics used to measure ESG performance relate to processes vs. outcomes, see Delmas and Blass (2010).

[2]We use Refinitiv scores despite the time inconsistency issue mentioned in Berg et al. (2021) because these scores are widely used in the ESG literature.

2.2 IBES

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

To match the monthly IBES consensus forecasts to the RepRisk data, we aggregate all the RepRisk ESG incidents that occurred between two summary statistic dates to the monthly level. Specifically, for two consecutive consensus forecast summary statistic dates d_{t-1} and d_t, we consider ESG incidents occurring on dates within $[d_{t-1}, d_t)$ to be the number of ESG incidents in month t, and we create two variables: an indicator variable equal to one if there is at least one incident in month t (*incidents*) and a variable that counts the number of incidents occurring in month t (*num_incidents*).

2.3 Stock returns, fundamentals and other events

We collect daily US stock returns from the Center for Research in Security Prices (CRSP) and the daily stock returns of international firms and firm fundamentals from Compustat. We merge the CRSP/Compustat data with IBES using the last trading day before the IBES consensus forecast date. For US companies, we match the CRSP/Compustat data with IBES using CUSIP numbers. For international companies, we match the Compustat data with IBES using SEDOLs. We merge the Compustat data with IBES using the last observable financial statement on the consensus forecast date. We consider a financial statement to be observable only after the earnings announcement (or publication) date rather than the fiscal year end date to avoid look-ahead bias. To make firms in the international sample comparable, we convert all currencies to US dollars using daily exchange rates.

In some of the tests, we use the advertisement expenditure of firms, which is only available for the US sample but is still missing for a large fraction of that sample. We first construct firm-level advertisement intensity, which is defined as advertisement expenditures scaled by revenues. We then take the median advertisement intensity of each industry (GICS2) as the industry-level advertisement intensity and assign that measure to all the firms in the relevant industry. We merge the CRSP-Compustat-IBES sample with the RepRisk data using ISINs. We require that the firm exists in all the data sources to be included in the final sample.

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

2.4 Construction of key variables

Our analysis focuses on changes in forecasts. For EPS forecast $F_t EPS_{t+h}$ made in month t for horizon h, we define the change in the EPS forecasts between months $t-1$ and t as $\Delta F_t EPS_{t+h} = F_t EPS_{t+h} - F_{t-1} EPS_{t+h}$. Similarly, the change in PTGs is defined as $\Delta PTG_t = PTG_t - PTG_{t-1}$. 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 $\Delta F_t Sales_{t+h} = F_t Sales_{t+h} - F_{t-1} Sales_{t+h}$ and the change in gross margin forecasts as $\Delta F_t GrossMargin_{t+h} = F_t GrossMargin_{t+h} - F_{t-1} GrossMargin_{t+h}$. In the regressions we will scale the forecast change by initial forecasts, i.e., using $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})}$, $\frac{\Delta PTG_t}{PTG_{t-1}}$, $\frac{\Delta F_t Sales_{t+h}}{F_{t-1} Sales_{t+h}}$ and $\frac{\Delta F_t GrossMargin_{t+h}}{abs(F_{t-1} GrossMargin_{t+h})}$ as dependent variables.[3] Since LTG forecasts are already in percentage terms, we directly use the change $\Delta LTG_t = LTG_t - LTG_{t-1}$ as the dependent variable.

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

Our final sample spans from 2008 to 2019, including 81,749 ESG incidents of 9,737

[3]For earnings forecasts we scale by the absolute value of initial earnings forecast to address negative forecasts. In our sample, 5.5% of earnings forecasts have negative values. Our results are unchanged if we eliminate these observations.

firms from 49 countries or regions.[4] Our sample includes 744,858 unique firm-month observations, out of which 10.44% of firm-months have at least one incident (6.57% have exactly one incident and 3.87% have at least two incidents) and on average 0.23 ESG incidents happen in each month.[5] There are 2,976,889 firm-month-horizon level EPS forecasts, 2,831,931 firm-month-horizon level sales forecasts, 1,442,110 firm-month-horizon level gross margin forecasts, 688,899 firm-month level PTG forecasts, and 253,735 firm-month level LTG forecasts. In the full firm-month-measure-horizon panel sample, 7.57% of observations have exactly one ESG incident, and 4.82% of observations have at least two ESG incidents. Table 2 reports the summary statistics of the main variables used in the analysis.

Table 2 about here.

3 Analysts' Reactions to ESG incidents

To examine how analysts react to ESG incidents, we conduct panel regression analysis for different forecast horizons. The objective is to understand first whether analysts believe that ESG incidents affect future cash flows and, second, the term structure

[4]The countries (regions) include the United States, Japan, China, Korea, Canada, the United Kingdom, India, Taiwan, Australia, Germany, France, Brazil, the Cayman Islands, Sweden, Switzerland, Malaysia, Norway, Finland, Spain, Italy, Hong Kong, South Africa, the Netherlands, Indonesia, Bermuda, Thailand, Mexico, Denmark, Singapore, the Philippines, Turkey, Poland, Belgium, Russia, Austria, New Zealand, Chile, Israel, Nigeria, Portugal, Pakistan, Greece, Ireland, Luxembourg, Egypt, Kenya, Colombia, Argentina, and Vietnam. Table IA.2 shows how the sample is distributed across countries.

[5]In RepRisk, one incident could relate to multiple firms. Our sample includes 173,123 unique firm-incidents.

of this effect, i.e., whether ESG incidents have only a short-term effect (i.e., at the quarterly or one-year horizon) on profits or instead reflect issues that will materialize mostly over longer horizons (that is up to three years ahead). For this analysis, we consider the forecasts for different horizons separately. Specifically, we use forecasts for the one-quarter to three-year horizons and estimate the following regression for each horizon h:

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

The dependent variable is the change in the consensus EPS forecasts between two consecutive months $t-1$ and t, scaled by the absolute value of the consensus EPS forecast in month $t-1$. We also consider changes in long term growth forecasts LTG, as well as analyst implied returns based on price targets, which we calculate as the change in the consensus PTG between months $t-1$ and t scaled by the PTG in month $t-1$, as well as realized returns. 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 cumulate ESG incidents to give both the market and the analysts enough time to react to them. In unreported results, in which we explore the effect of past incidents on currrent reactions, we find that incidents affect analyst forecast changes for up to 12 months, while the market reacts more quickly to these incidents. Our results are robust to aggregating the ESG incidents over months $[t-3,t]$, $[t-9,t]$ or $[t-12,t]$. The results of these robustness tests are reported in Table IA.3.[6]

We include firm fixed effects (σ_i in Eq. 1) in these regressions, so that the tests exploit only time variation within firms. This allows us to deal with the possibility that some firm characteristics (e.g., size) are correlated with analyst forecast revisions and also with the occurrence of ESG incidents (e.g., through media coverage intensity). We also include Industry × Country × Month fixed effects ($\gamma_{Country \times Industry \times t}$ in Eq. 1) which absorb any country-level analyst forecast characteristics, any industry-level analyst forecast characteristics, and any time variation in analyst forecast revisions (e.g., due to changes in macroeconomic conditions), as well as the interaction of these effects. We double cluster standard errors at the firm and month levels to account for possible dependence across firms and months.

Table 3 about here.

Panel A of Table 3 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 (-0.142 %) is roughly equal to that for the two- or three-year horizons (-0.148 and -0.157 %, 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 on the forecasted long-term growth (LTG) of EPS is economically and statistically insignificant. The

[6] Gloßner (2021) also documents that firms' ESG incidents are serially correlated and that market participants tend to react slowly to these incidents.

last two columns of the table report the relative change in PTGs and stock returns following ESG incidents. The two effects are significantly negative and of similar magnitudes. Analysts' downward adjustments of price targets (Column 9) are of a similar magnitude as observed price movements following ESG incidents (Column 10).[7]

In Panel B of Table 3, we refine the analysis by considering how the number of incidents 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 compared to firms for which RepRisk reports only one incident. For example, decreases in EPS forecasts vary from approximately -0.001% to -0.119 % across all forecast horizons for firms with one incident in months $[t-6, t]$, while they vary between -0.113% and -0.277 % 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 as reported by RepRisk, have changes in the EPS forecasts of analysts that are roughly constant across all horizons.

[7] Our results are robust to alternative specifications. For example, the results hold when replacing month $\times$ industry $\times$ country fixed effects with only month $\times$ industry, month $\times$ country, or simply month fixed effects. Similarly, dropping firm fixed effects and adding firm-level controls leads to very similar conclusions. Our results are also robust to adding firm-level time-varying controls, which addresses the concern that some time-varying firm characteristics are correlated with analyst forecast revisions and with ESG incidents. Our analysis does confirm that ROA change, size and Book-to-Market predict changes in analyst forecasts, consistent with Das et al. (1998) and Engelberg et al. (2020)). Our analysis is also robust to controlling for changes in firm fundamentals, and the results also hold when scaling the EPS revisions by book value per share in the previous year, rather than lagged EPS forecasts. These robustness tests are presented in Internet Appendix Tables IA.4, IA.5, IA.6, IA.7 and IA.8.

Table 4 about here.

Table 5 about here.

We further explore heterogeneous effects across incident types. Table 4 reports analyst reactions to incidents in the E, S, and G categories separately. The impact of E incidents on forecast changes appears to be less significant than that of incidents concerning S and G matters, and S incidents appear to have stronger impact than G incidents. The insignificance of E incidents may be due to the fact that E incidents are less serious on average than those in the two other categories. In Table 5, we repeat the same exercise separately for firms with one or at least two incidents in each category. As in our previous tests, multiple incidents in any category have a larger impact on analyst reactions.

Table 6 about here.

We also examine the effect of incidents by levels of novelty, severity, and reach provided by RepRisk. We define high- and low-novelty (severity/reach) incidents if the level of novelty (respectively, severity, reach) is above or equal to two. Table 6 shows the effects of high- and low-novelty (respectively, severity, reach) incidents on analyst and market reactions. Incidents with high levels of novelty, severity, or reach have significantly negative effects on analyst forecasts at most horizons. On the contrary, the coefficients on low-novelty and low-severity incidents are only significant at the

1-year and 3-year forecast horizon respectively and are not significant for low reach incidents. This confirms that the baseline effect is mainly driven by severe, novel, and high-reach incidents.

If ESG incidents affect the reputation of firms vis-à-vis their customers, they can have long-term effects on cash flows as reputation is an intangible asset that takes time to build. To explore this possibility, we compare the term structure of analysts' reactions to ESG events with that of reactions to other negative informational shocks. To do so, we estimate the same regression as in Equation 1 but replace the ESG incident variable with a variable capturing the occurrence of other types of negative events reported in the Capital IQ Key Developments (KD) database. Out of the 153 types of events that Capital IQ reports, we identify 33 types that have a significantly negative impact on firms' earnings forecasts over a one-year horizon. Table IA.9 reports the detailed estimates of the impact of these negative events across different forecast horizons.[8] In terms of absolute value, the impact of ESG incidents are still smaller than other KD incidents, which is perhaps not surprising as intuitively the negative KD incidents are more financially material.

To compare the term structure effects of different events, we estimate their impact on earnings forecasts at different horizons as we do in Table 3. We then normalize the

[8]Note that the impact of ESG incidents on EPS forecasts documented in Table 3 is robust to controlling for other types of negative incidents in Capital IQ's Key Developments database. Figure IA.1 reports the effect of ESG incidents on one-, two-, and three-year EPS forecasts and returns after controlling for the occurrence of other types of incidents (one type at a time). The effects of ESG incidents on EPS forecasts and return are remarkably similar to those obtained in the baseline regression (Table 3) economically and statistically. This suggests that Reprisk's ESG incidents are not redundant with the other types of incidents reported in the Capital IQ database. We also control for all the Key Developments incidents simultaneously. As shown in Table IA.10, the results remain robust and the magnitude is comparable to the baseline results without these controls.

estimated impact coefficients by their impact at the one-year horizon and represent them graphically in Figure 2.

Figure 2 about here.

As shown in Figure 2, the impact of ESG incidents on EPS forecasts persists over longer horizons than that of other negative corporate news. On average, the impact of an ESG incident on earnings forecasts over the three-year horizon is about 21% higher (0.157/0.130=1.21, from Table 3) than the impact of an ESG incident on one-year earnings forecasts. By contrast, the impact of other types of events diminishes over time. For example, for credit rating downgrades, the impact on 3-year earnings forecasts is 42% lower (0.84/1.46=0.58; see Appendix Table IA.9) than the impact on 1-year earnings forecasts. A similar term structure appears when we use a regression setting. Specifically, we run the following regression:

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

Table 7 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 0.39% for 2-year forecasts and 0.29% for 3-year forecasts. These differences are significant, as shown in the pooled regressions in columns (4) and

(5). In contrast, the difference in the impact of ESG incidents across horizons is not significant (Columns 4 and 5). The F-tests in columns (4) and (5) show that there is a significant difference between the term structure of ESG incidents and that of average negative KD incidents. We conclude that ESG incidents have a longer-lived impact on earnings forecasts than other types of negative incidents.

Table 7 about here.

4 Economic mechanism: Sales vs. costs

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

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

Table 8 about here.

Table 8 reports the results of these regressions. The analysis suggests that the anticipated decrease in earnings documented earlier is driven by a decrease in both expected sales and expected profit margin. In terms of magnitudes, the reduction in EPS appears to be primarily driven by a reduction in sales. The coefficients on the ESG incident dummy variable are consistently negative and statistically significant over most horizons (see columns (1)-(7) of Panel A), in which we use changes in expected sales as the dependent variable. Columns (1)-(7) of Panel B suggest that this effect is more pronounced for firms with multiple incidents, similarly to the effects on earnings forecasts.[9] In contrast, the coefficients on the ESG incident dummy variable in the gross margin regressions (in columns (8)-(14) of Panel A) are only significant at the 1-quarter, 1-year, and 2-year horizons. In addition, in terms of magnitudes, the coefficients in the gross margin regressions are smaller than those in the sales regressions. Based on the estimation using annual forecasts, following an ESG incident, expected sales decrease by around 0.051% ($\frac{0.036+0.055+0.061}{3}$), and expected gross margin decreases by 0.023%($\frac{0.027+0.028+0.013}{3}$). Thus, the decrease in expected sales following an ESG incident is around twice as large as the decrease in expected gross margin. The difference in magnitude also shows up when considering

[9] The result is robust to scaling the change in sales forecasts by lagged book value instead of lagged sales forecasts. The results are shown in Appendix Table IA.11.

multiple incidents in Panel B. This divergence between sales and margin forecasts is not caused by a difference in numbers of observations, as confirmed in Appendix Table IA.12 using a balanced sample.

To compare the impact of ESG incidents and other Key Development incidents on expected sales, in Appendix Table IA.13 we report the results of regressions similar to Equation 2, replacing the dependent variable with changes in sales forecasts $\frac{\Delta F_t Sales_{i,t+h}}{F_{t-1} Sales_{i,t+h}}$. The ESG incidents have a longer-term impact on sales forecasts compared to other incidents. This result suggests that the longer-term impact of ESG incidents on EPS forecasts (compared to other incidents) comes from the longer-term impact on sales forecasts.

Overall, these results suggest that the impact of ESG news on earnings forecasts is likely to primarily come from a customer channel, i.e., analysts expect customers to avoid buying from firms that fail to comply with ESG standards.[10] This finding is consistent with Duan et al. (2022) and Houston et al. (2023), which use retail store data to show that consumer demand decreases following negative ESG incidents. Analysts are able to incorporate the lower future consumer demand by adjusting sales forecasts after the occurrence of negative ESG incidents.

[10]One may worry that the drop in sales is driven by employees' behavior (e.g. strike or factory shutdown). To address this concern, we run our baseline regressions but only consider ESG incidents that are not associated with the four types of employee-related incidents ("poor employment conditions", "supply chain issues", "freedom of association and collective bargaining", and "occupational health and safety issues"). As shown in Table IA.14, our results remain robust in both statistical and economic terms.

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

There are two potential reasons why stock values decrease after the occurrence of negative ESG events. The first is downward revisions in expected future earnings. The second is that the cost of capital might have increased, reflecting a smaller set of available investors (as some investors exclude firms with low ESG performance) or a higher level of perceived systematic risk. In this section, we propose an empirical decomposition of the valuation effects of ESG shocks by disentangling the effects of changes in forecasted profits from the effects of changes in discount rates.

5.1 A first intuitive pass using Gordon's formula

The results in Table 3 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:

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

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), $F_t EPS_{i,t+1}$ is the time t forecast of the next twelve months' earnings, r_{it} is the discount rate of firm i at time t, and g_{it} is the expected growth rate of earnings of firm i at time t. The theoretical firm-level return induced by an ESG information shock is:

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

In our data, Table 3 suggests that the impact of ESG incidents leaves expected growth unchanged ($\Delta g \simeq 0$), while the similarity of the coefficient in Column (10) of Table 3 to the coefficients in columns (5)-(7) translates to $\frac{\Delta PV_{it}}{PV_{it}} \simeq \frac{\Delta F_t EPS_{i,t+1}}{F_t EPS_{i,t+1}}$. This implies that changes in expected future earnings explain most of the changes in firm equity values induced by a typical ESG incident.

5.2 A discounted dividends approach

We now aim to confirm the result sketched above through a somewhat more sophisticated valuation framework than that of the Gordon formula. We rely on the same simple firm-level discounting approach as in Hommel et al. (2023), in which we use information on the term structure of earnings forecasts. Specifically, for each firm i at date t, we define the present value of its future payout per share as:

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

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

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

where P_{it} is the stock price of firm i at time t. We keep only the values of this discount rate r_{it} that are between 0 and 30%. Our null hypothesis is that changes in EPS forecasts following ESG incidents can account for changes in firm values.

To better take into account the under-reaction of analysts and the potential difference in the speed of reaction between analysts and the market, we conduct an event study for the discount rate analysis in this section. Specifically, we define ESG incidents in a month as an "event" and investigate how analyst forecasts, return, price targets and implied discount rate change following an event. We run the following regression

$$y_{t,t+s} = \alpha + \beta\, \mathbb{1}\{ESG\ incidents\ in\ month\ t\} + \gamma_{Country \times Industry \times t} + Controls + \epsilon_{i,t} \tag{5}$$

where $s = 0, 1, 2, ..., 6$ indicates the window (in months) following an incident. $s = 0$

indicates the contemporaneous month when the incident happens. To capture value change from updated EPS forecasts, we calculate the new firm value using the formula above with updated analyst forecasts in month $t+s$ 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 $t+s$, $\frac{\widehat{PV_{i,t+s}}-PV_{i,t-1}}{PV_{i,t-1}}$, which is the predicted stock return if ESG shocks affect only expected profitability but not the discount rate. $y_{t,t+s}$ is the value change implied by the change in EPS forecasts (in column 1), the return (in column 3), or the implied discount rate change (in column 5) between months t and $t+s$. The main independent variable of interest is a dummy variable indicating whether any ESG incident happened in month t. Control variables include size and book to market ratio quintiles of firms.

Table 9 about here.

The results are shown in Table 9. Each column shows the estimated β from the regression above and the corresponding t-statistics. In the contemporaneous month, market reaction is -0.24% (column 3), while the implied value change from EPS forecast reaction is only -0.08% (column 1). Such reactions jointly imply a contemporaneous change in discount rate $\frac{\Delta r}{r}$ of 0.05% (column 5), which is also statistically significant (t=2.08). This is due to analysts reacting slower than the market. Over wider windows post-event, the implied value change from EPS forecast reaction becomes larger. After 3 months ($[t, t+3]$), the analysts' reaction is -0.41% (column 1) and the market return is -0.30% (column 3). As a result, the inferred discount change is equal to -0.01% (column 5) and statistically nonsignificant (t=-0.11). Implied changes in discount rates keep decreasing but remain insignificant as we expand the window to $[t, t+6]$. The conclusion is that the change in EPS forecast can account for all the changes in market return, even if the discount rate does not change. A regression analysis similar to Equation 1 leads to similar conclusion, as shown in Appendix Table IA.15.

To summarize, cash flow effects are large enough to explain observed changes in firm valuations following ESG incidents. The change of implied discount rate is not statistically significant and is tiny in magnitude.[11] One caveat is that our test of discount rate changes may lack statistical power and therefore we cannot fully rule out a change in discount rates.

6 Heterogeneity

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

[11] A limitation of this estimation is that we only run the IRR analysis for the US sample. Although later analyses in Section 6.1 suggest that the effects do not differ between different areas, ESG incidents could potentially affect discount rates differently outside the US.

6.1 Variation across geographic regions

First, we analyze the heterogeneity across countries, splitting the sample by geographic region. It is possible that the downward adjustment in sales and earnings forecasts varies across regions, for instance because of geographic differences in consumer preferences. To test this hypothesis, we use firms located in North America (the US and Canada) as the base category and further interact the ESG incident variables with dummies indicating $EU15$, $Asia$, and $Others$, where $EU15$ marks the 15 most developed countries in Europe as defined by the United Nations[12] and $Others$ mostly includes firms in South America, Australia, and Africa. We focus on annual forecast data, as quarterly forecasts are predominantly available for US firms.

Table 10 about here.

Panel A of Table 10 reports the effects of ESG incidents on EPS, PTGs, and returns across regions. At 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 the *Other* geographic regions are weakly significant and positive, which implies that the 3-year earnings forecasts for firms in the *Other* region react less to ESG incidents than in other geographic areas. There is not much difference in terms of the reaction in PTGs.

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

In 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 10 reports the heterogeneous effects on the sales forecasts of firms by geographic region. There is no significant evidence difference across regions in sales forecasts, which is broadly consistent with the results for the earnings forecasts. 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 firms in *Other* geographic regions than for North American firms over longer forecast horizons.

6.2 Variation across industries

Next, we ask whether the link between ESG-related news and analyst forecast revisions is stronger in some industries. Industries vary significantly in their exposure to ESG events. The average number of incidents per industry appears in Figure 3, which shows, for example, that firms in the energy sector are more likely to have ESG incidents in the average month than firms in the real estate sector.

Figure 3 about here.

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 3 above. We consider the average sensitivity of one-, two-, and three-year earnings forecasts to RepRisk news across all firms in each industry (as defined by GICS2 codes) as our industry measure of ESG sensitivity.

Figure 4 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 four industries in which the analysts are most sensitive to negative ESG incidents are "Communication Services" "Consumer Durables & Apparel", "Commercial & 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 5 is similar to the ranking presented in Figure 4.

Figure 4 about here.

$\boxed{\text{Figure 5 about here.}}$

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 6 plots the advertising intensity of the various industries (measured as $\frac{\textit{Advertisement Expense}}{\textit{Revenue}}$) against the industry-level sensitivity of analyst forecasts to news, i.e., the industry-level average of the coefficients obtained in Table 3 . Panel A of Figure 6 illustrates the sensitivity of earnings forecasts to ESG-related news, while Panel B illustrates the sensitivity of 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 3). In Table 11, we split the industries into two groups, B-to-C and B-to-B, according to whether the firm belongs to an industry that is above or below the median of all industries in terms of its advertising expenditure. We then repeat the baseline analysis of Equation 1, adding to the regression the interaction between a dummy measuring high advertisement intensity and the indicator variable equal to one for firms experiencing ESG incidents. Though we do not find a statistically significant interaction coefficient between ESG incidents and the dummy identifying B-to-C industries according to advertisement expenses, the magnitude is economically meaningful over the one- and two-year horizons (Panel A), which implies the impact in B-to-C industries is almost twice as large as B-to-B industries. Panel B of Table 11 also suggests that sales forecast revisions after ESG incidents are stronger for firms in B-to-C industries over one- and two-year horizons.

Figure 6 about here.

Table 11 about here.

6.3 Large vs. small firms

We also analyze whether there is heterogeneity by firm size, which we measure using market capitalization. We split the sample into small and large firms. The incidence of RepRisk ESG news items is highly correlated with firm size. Figure 7 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 tenth decile on average have 1.2 more incidents per month than firms in the first decile. Therefore, ESG news could possibly be too rare for any effect on small firms to be detectable. On the other hand, investors closely monitor the ESG performance of large firms and could anticipate ESG-related events before they are known to the wider public. In Table 12, 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 3 for the two groups of firms. The results show that the effect of ESG events on analyst forecasts is stronger for small firms. The coefficient on the interaction between ESG events and the dummy variable equal to one for large firms compensates a large part of the coefficient on the event variable alone. In Panel B of Table 12, we repeat the same analysis for sales forecasts. Analysts' downward revaluations of future sales that we document above seem to be slightly stronger for smaller firms. Overall, these results suggest that the information content of RepRisk events appears to be more relevant for smaller firms.

Figure 7 about here.

Table 12 about here.

7 Are analysts correct in reacting to negative ESG news?

Analysts downward adjust their earnings and sales forecasts following negative ESG incidents. In this section, we examine whether analysts are correct in making these adjustments or whether they tend to overreact to ESG news. We start by testing whether ESG incidents affect realized firm fundamentals. We aggregate ESG incidents at the annual level and test whether ESG incidents in a year affect realized earnings, sales, and gross margin over the following years. Specifically, we estimate the following regression equation:

$$\begin{aligned}\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} &= \alpha + \beta\,\mathbb{1}\{ESG\ incidents\ between\ year\ t-1\ and\ t\} \\ &\quad + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}\end{aligned} \tag{6}$$

where $Y_{i,t}$ denotes realized annual earnings, sales, or gross margins at the end of year t of firm i and $h = 0, 1, 2$ indicate the current, one-year, and two-year horizon. The main independent variable is a dummy variable equal to one if there is any ESG incident between the end of year $t - 1$ and the end of year t. We control for country $\times$ industry $\times$ year fixed effects and firm fixed effects, similar to our baseline specification of Equation 1.

Table 13 about here.

The results are presented in Table 13. Panel A shows that, on average, having ESG incidents reported in a year decreases firms' realized net income by 8.8% - 11.8% (columns 1-3), and decreases firms' realized sales by 1.2% - 4.2% (columns 4-6). By contrast, the effect on realized gross margin is not significant at all horizons. In Panel B, we split the independent variable by low and high number of incidents based on the median number of incidents in a given year. The effect is stronger when there is a high number of incidents in a year, which is consistent with our baseline regressions using analyst forecasts. The preceding analysis shows that firms' realized earnings and sales decrease after negative ESG incidents. This implies that analysts are correct when they downward adjust their forecasts following negative ESG news.

To further elaborate on this point, we turn to analyst-level forecasts and ask whether reacting to ESG incidents makes analysts more accurate in their EPS forecasts. Specifically, we first collect individual analyst-level forecasts and forward fill the forecasts to the monthly level to keep a similar data structure compared to consensus-level forecasts[13]. Then, we run the following regressions using the analyst-firm panel:

$$
\begin{aligned}
\frac{|FEPS_{i,e,j,t} - EPS_{i,e}| - |FEPS_{i,e,j,t-1} - EPS_{i,e}|}{|EPS_{i,e}|} = \alpha + \eta DownwardAdj_{i,e,j,t} \\
+ \beta DownwardAdj_{i,e,j,t} \times \mathbb{1}\{ESG\ incidents\ of\ firm\ i\ in\ [t-6,t]\} \\
+ \gamma_{i,e,t} + \epsilon_{i,e,j,t}
\end{aligned} \tag{7}
$$

where $FEPS_{i,e,j,t}$ is the EPS forecast made for the earnings announcement e of firm i by analyst j in month t.[14] $EPS_{i,e}$ is the realized earnings of firm i for earnings announcement e. $DownwardAdj_{i,e,j,t}$ is a dummy variable indicating if analyst j downward adjusts her EPS forecast from month $t-1$ to month t, i.e. $FEPS_{i,e,j,t} - FEPS_{i,e,j,t-1} < 0$. $\gamma_{i,e,t}$ indicates firm $\times$ earnings announcement $\times$ month of forecast fixed effects. Intuitively, this regression is comparing analysts who issue EPS forecasts for the *same* firm's earnings announcement e in the *same* month, and tests whether the analysts who downward adjust EPS forecasts following ESG incidents see a decline in their forecast error, compared to analysts who do not downward adjust their EPS forecasts.

Table 14 about here.

The results are presented in Table 14. The coefficient estimates on $DownwardAdj$ are negative and significant, which captures the baseline effect that analysts are on average over-optimistic and any downward adjustment leads to a lower forecast error.[15] The coefficients of the interaction term are our coefficients of interest. They

[13] We only forward fill if the forecasts are not older than one year.

[14] e denotes one specific firm-level earnings realization, e.g., the earnings of fiscal year 2015.

[15] See, for example, Das et al. (1998) for more detailed discussion on analysts' over-optimism.

are negative and significant for annual forecasts and weakly significant for quarterly forecasts. This suggests that after negative ESG incidents, analysts who downward adjust EPS forecasts decrease forecast error further than when there is no ESG incident, compared to analysts who do not downward adjust their EPS forecasts.

To sum up, realized earnings decrease after ESG incidents. Moreover, the analysts who downward adjust earnings forecasts reduce forecast error compared to the analysts who do not. The two pieces of evidence suggest that it is correct to downward adjust earnings forecasts after the occurrence of negative ESG incidents.

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 (from one quarter) and longer horizons (up to three years). These downward revisions are mostly due to negative revisions of future sales forecasts, suggesting that analysts expect consumers to react negatively to deteriorating ESG performance. We also provide evidence that stock prices react negatively to the occurrence of negative ESG news. Interestingly, most of the negative impact on stock prices from these ESG news items is quantitatively explained by changes in earnings forecasts. Analysts are correct in making the forecast revision after ESG incidents. Analysts who downward adjust forecasts decrease forecast error compared to those who do not, suggesting that the integration of ESG concerns is actually rational rather than a "fad".

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

Appendix A: RepRisk vs. other ESG data

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

To verify that despite the reservations about ESG scores discussed above, there is indeed a link between RepRisk news and changes in ESG ratings, we compare the RepRisk news items with the scores provided by three of the most influential ESG rating agencies, namely, Refinitiv (previously Asset4), MSCI, and Sustainalytics. For Refinitiv, we use the "Equal-weighted Rating". For MSCI, we use the "Industry Adjusted Score". For Sustainalytics, we use the "Total ESG Scores". Note that Berg et al. (2021) point out the rewriting history issue of Refinitiv. We use Refinitiv score anyway as it is a widely used ESG dataset. 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:

$$ESG\,Score_{i,t} = \sum_{s=0}^{12} \beta_s log(num.\ ESG\ incidents_{i,t-s}) + \gamma_i + \delta_{t \times Industry} + \epsilon_{i,t}, \quad (8)$$

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. We cluster the standard errors at the firm and month levels to account for possible dependence across firms and months.

The results reported in Table 15 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 three 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 15 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 15 about here.

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Figures

Figure 1: Number of RepRisk ESG incidents by year

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

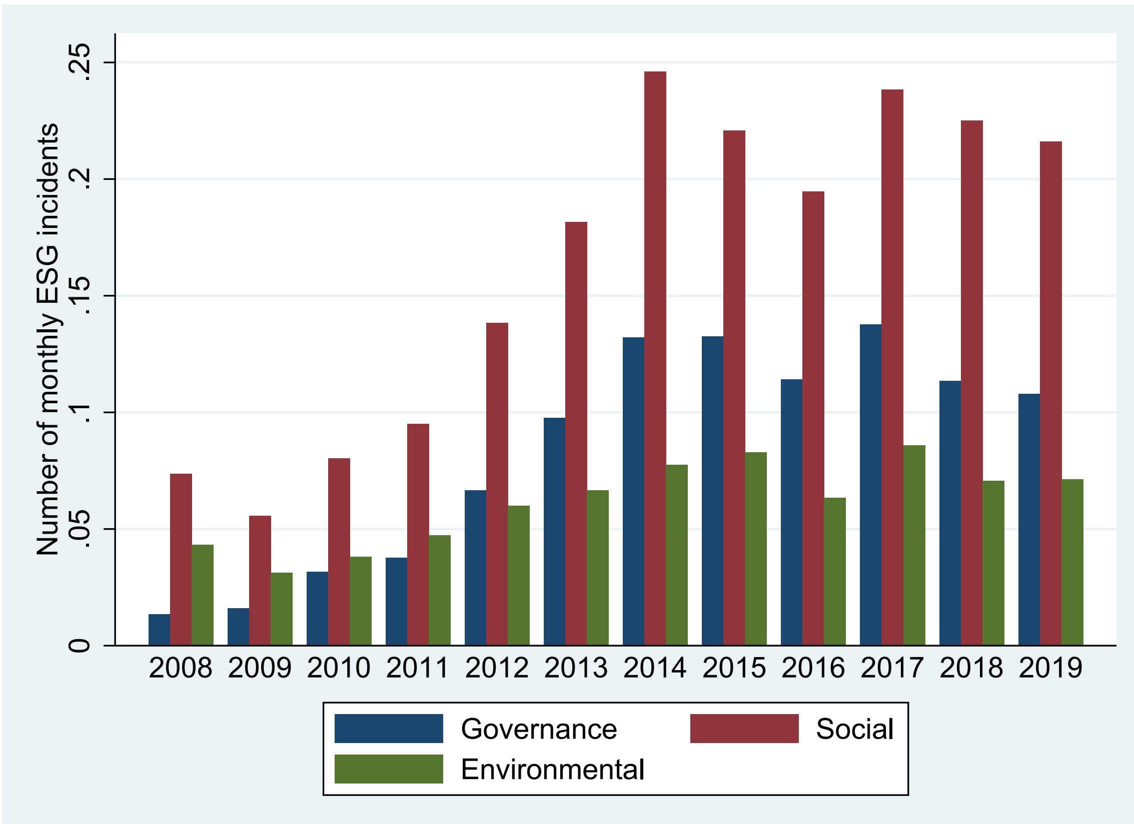


Figure 2: Term structure of the impact of incidents on earnings forecasts

This figure reports the term structure of different types of *negative* corporate events. For each event type u and horizon h, we estimate the regression equation $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta_h \mathbb{1}\{type\ u\ incidents\ in\ [t-6,t]\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$, where the dependent variable is the change in EPS forecasts scaled by the lagged absolute EPS forecasts. The independent variable is one if an event of type u happens in months $[t-6,t]$ and 0 otherwise. Detailed estimates for βs are shown in Appendix Table IA.9. Then, for each incident type and forecast horizon h, we scale the impact by its impact on the 1-year forecast. On the y-axis is the impact on earnings forecasts scaled by the 1-year forecasts. On the x-axis are the horizons (ranging from one to three years). The blue lines represent the term structure for each type negative events from the Key Developments database. The bold black line represents the average term structure of all negative Key Development events. It can be interpreted as follows: "on average, following a negative corporate event, the percentage revision of 2-year (3-year) forecasts is only 87% (60%) of that of 1-year forecasts". The bold red line represents the term structure of the ESG incidents. It can be read as follows: "on average, following a negative ESG incident, the percentage revision of 2-year (3-year) forecasts is stronger than that of 1-year forecasts by a factor of 1.14 (1.21)".

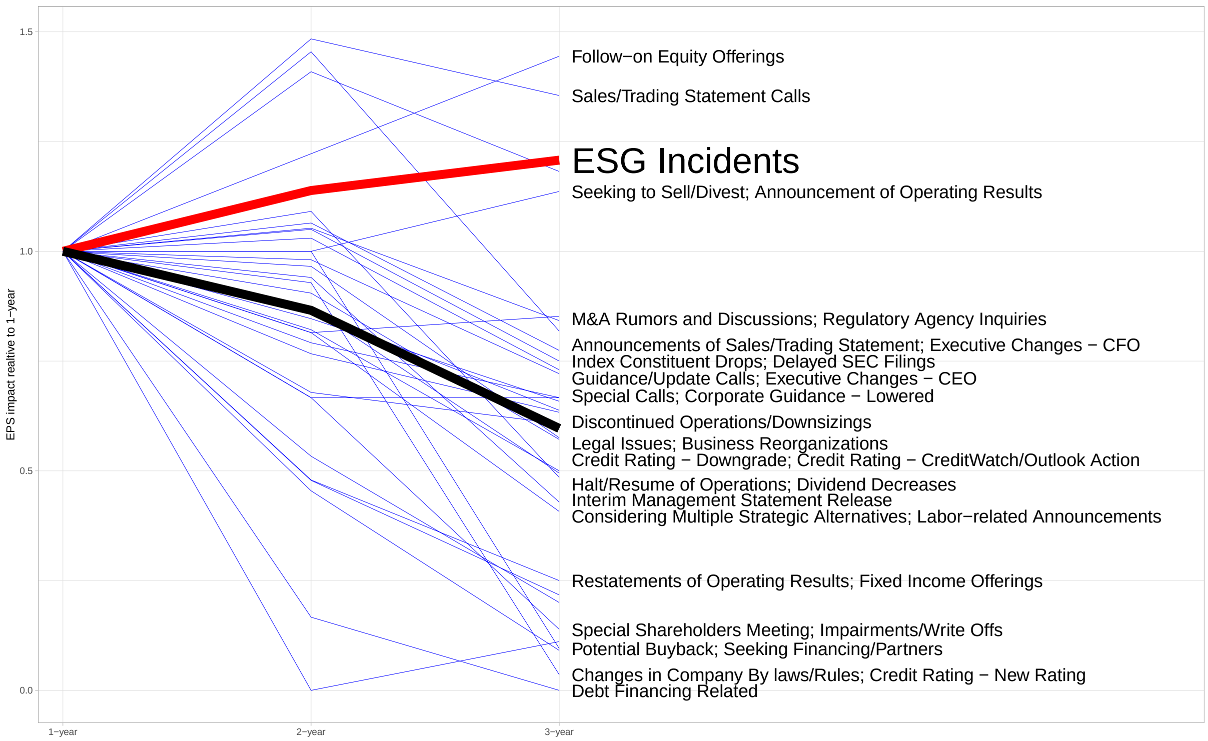


Figure 3: Number of incidents by industry

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

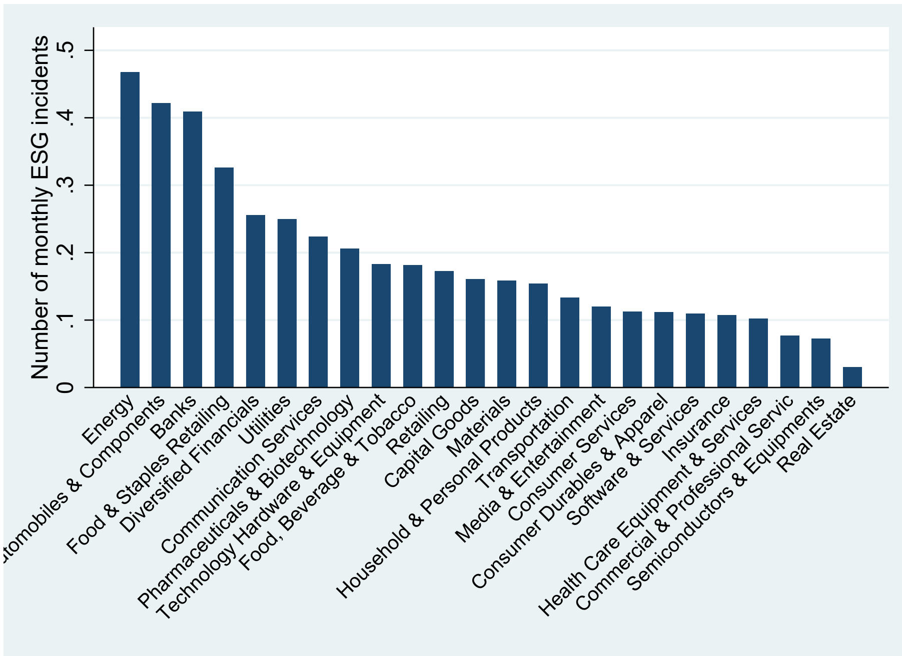


Figure 4: EPS sensitivity by industry

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

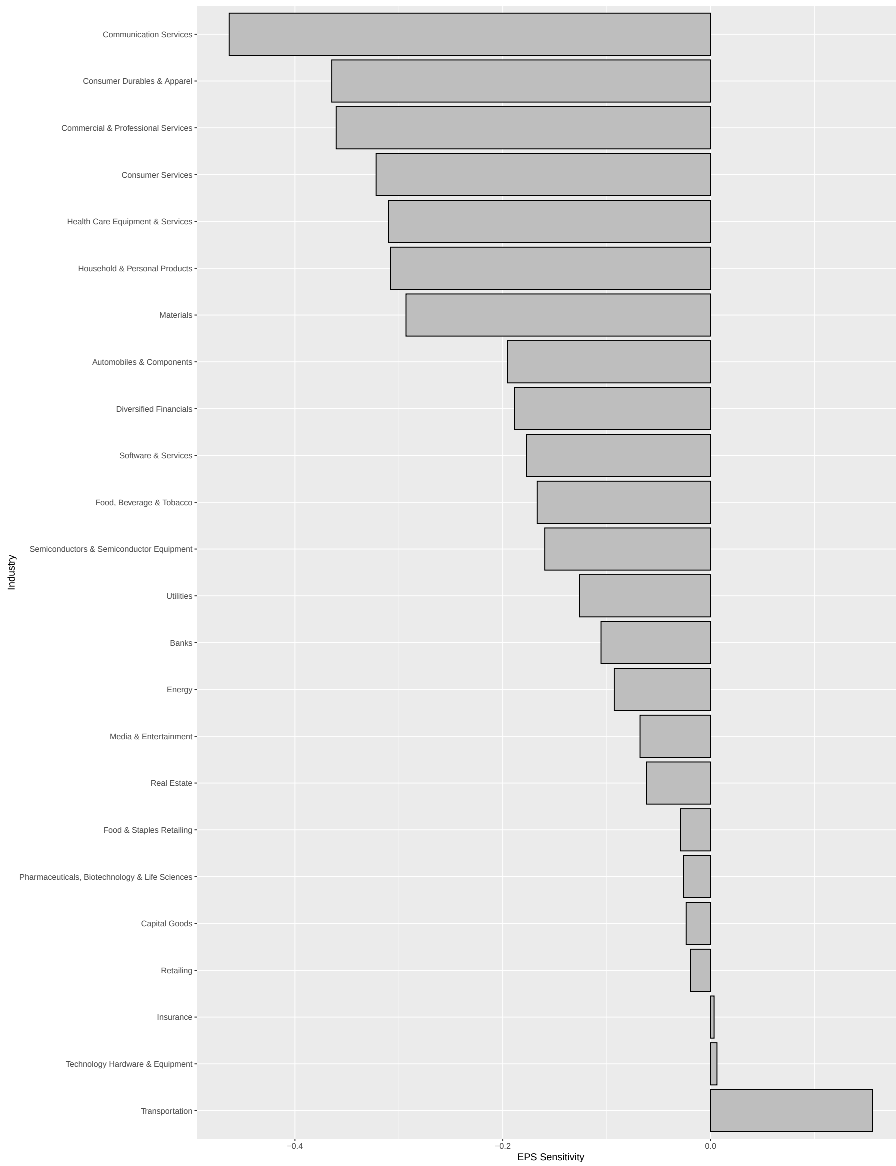


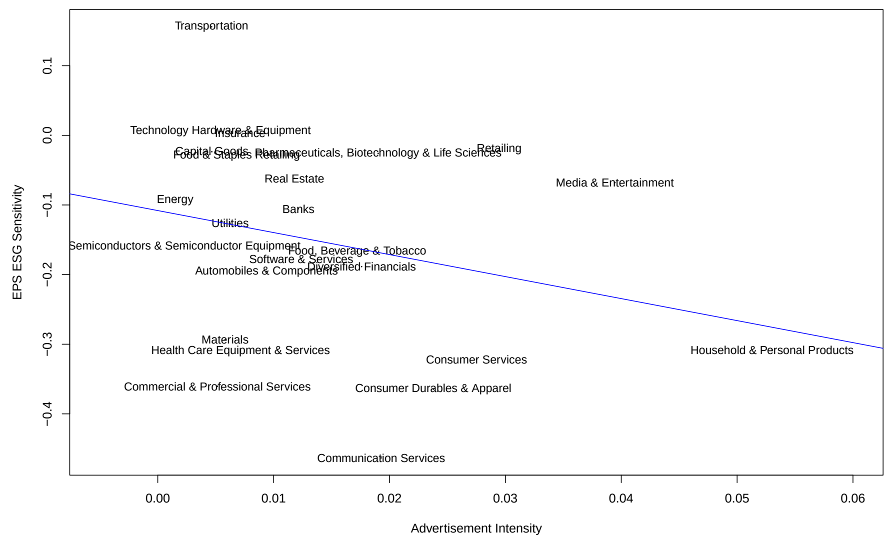
Figure 5: PTG sensitivity by industry

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 6: 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

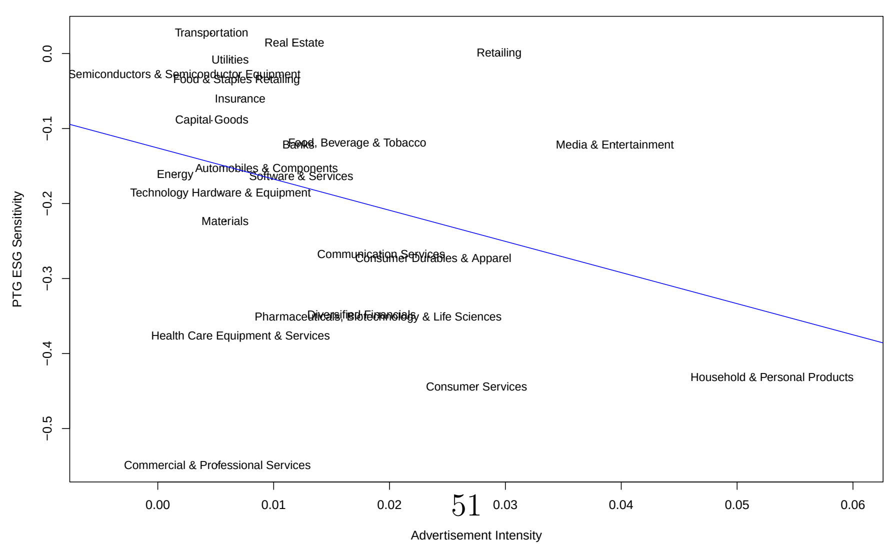
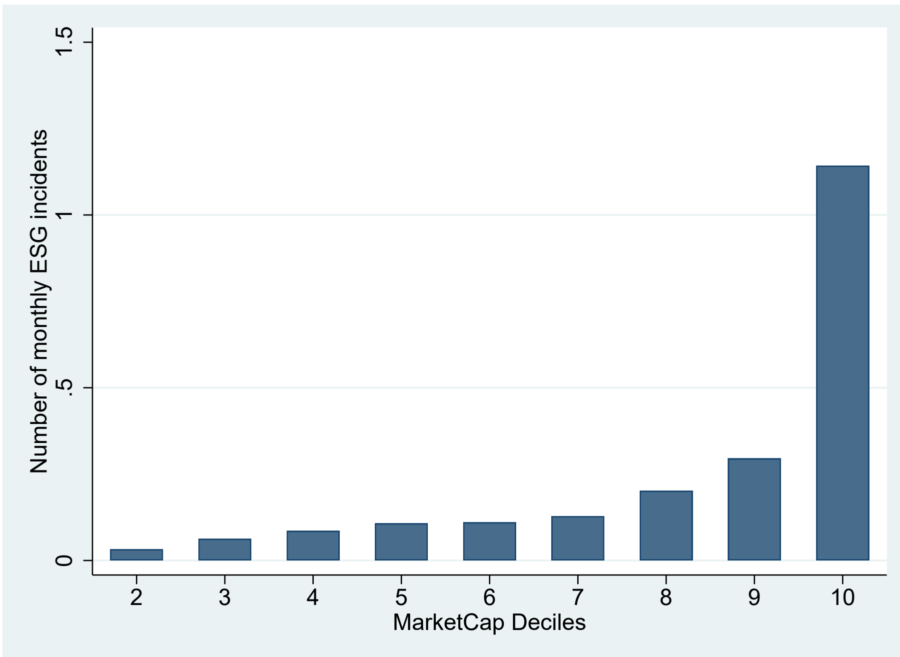


Figure 7: Number of incidents by firm size

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: Descriptive statistics of RepRisk Data

This table provides descriptive statistics of RepRisk data. Panel A reports the issues that RepRisk retains and their corresponding categories (E, S, or G). One RepRisk incident can be associated with multiple issues. Panel B reports the distribution of environmental, social, and governance incidents. Panel C reports the distribution of novelty, severity, and reach levels (ranging 1 to 3) provided by RepRisk. Numbers in Panel C represent, relative to all incidents, the percentage of incidents with a certain characteristic.

Panel A: List of ESG 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	

Panel B: Distribution of environmental, social and governance incidents

E	S	G	# incidents	Percent
1	0	0	4,198	5.14
0	1	0	28,354	34.68
0	0	1	7,304	8.93
1	1	0	15,933	19.49
1	0	1	464	0.57
0	1	1	23,044	28.19
1	1	1	2,450	3.00

Panel C: Distribution of novelty, severity and reach levels

	Novelty	Severity	Reach
1	0.40	0.68	0.29
2	0.60	0.31	0.55
3	0.00	0.01	0.16

Table 2: Summary statistics

This table reports the summary statistics of the main variables used in the 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
$\Delta EPS/EPS$ (%)	2,976,889	-1.23	8.31	-32.69	-1.46	0.00	0.04	20.00
ΔLTG (%)	253,735	-0.12	1.82	-6.30	0.00	0.00	0.00	5.32
$\Delta PTG/PTG$ (%)	688,899	0.22	5.68	-16.67	-0.56	0.00	1.45	16.67
Return (%)	737,689	0.35	9.93	-24.07	-5.18	0.55	6.13	23.42
$\Delta Sales/Sales$ (%)	2,831,931	-0.17	2.27	-7.68	-0.43	0.00	0.19	6.44
$\Delta GrossMargin/GrossMargin$ (%)	1,442,110	-0.13	1.94	-7.04	-0.06	0.00	0.00	5.72
Market Cap. (Bil USD)	8,193,510	10.14	28.88	0.08	0.98	2.73	8.10	133.22
ΔROA(%)	7,334,872	-0.00	0.11	-0.59	0.00	0.00	0.00	0.44
$\Delta(CapEx/Asset)$(%)	7,933,001	-0.01	0.21	-1.06	0.00	0.00	0.00	0.89
$\Delta(NetDebt/Asset)$(%)	7,915,217	0.01	0.56	-2.35	0.00	0.00	0.00	2.75
Any incidents	8,193,564	0.12	0.33	0.00	0.00	0.00	0.00	1.00
Num. of incidents	8,193,564	0.27	1.20	0.00	0.00	0.00	0.00	5.00

Table 3: Reaction of earnings forecasts to ESG incidents

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

Panel A: At least one incident

	(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 months [t-6,t]	-0.142**	-0.124*	-0.074	-0.049	-0.130***	-0.148***	-0.157***	0.002	-0.168***	-0.177***
	(-2.09)	(-1.85)	(-1.14)	(-0.83)	(-3.08)	(-3.76)	(-4.18)	(0.17)	(-6.20)	(-5.08)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Panel B: Splitting by the number of incidents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	LTG	PTG	Ret.
1 incident in months [t-6,t]	-0.082	-0.068	-0.001	-0.020	-0.090**	-0.110***	-0.119***	0.012	-0.132***	-0.167***
	(-1.15)	(-0.96)	(-0.01)	(-0.33)	(-2.12)	(-2.74)	(-3.11)	(0.93)	(-4.88)	(-4.83)
>=2 incidents in months [t-6,t]	-0.277***	-0.248***	-0.238**	-0.113	-0.222***	-0.236***	-0.240***	-0.019	-0.250***	-0.198***
	(-3.03)	(-2.79)	(-2.59)	(-1.27)	(-3.75)	(-4.39)	(-4.59)	(-1.21)	(-6.52)	(-3.99)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Table 4: Reaction of earnings forecasts to ESG incidents—By E/S/G category

This table reports the results of regressions of changes in EPS consensus forecasts, PTG, and returns 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 equal to 1 if any environmental incidents happen in months $[t-6, t]$ and 0 otherwise. In Panel B, the independent variable is equal to 1 if any social incidents happen in months $[t-6, t]$ and 0 otherwise. In Panel C, the independent variable is equal to 1 if any governance incidents happen in months $[t-6, t]$ and 0 otherwise. Standard errors are double clustered at the firm and month levels. 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 months [t-6,t]	-0.121	-0.029	-0.195**	-0.138	-0.100*	-0.109*	-0.094*	0.015	-0.083**	-0.080*
	(-1.23)	(-0.32)	(-2.10)	(-1.51)	(-1.70)	(-1.92)	(-1.77)	(0.89)	(-2.46)	(-1.70)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

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 months [t-6,t]	-0.149**	-0.194***	-0.125*	-0.077	-0.175***	-0.189***	-0.180***	0.002	-0.169***	-0.142***
	(-2.15)	(-2.99)	(-1.92)	(-1.20)	(-4.23)	(-4.86)	(-4.77)	(0.14)	(-6.13)	(-4.08)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

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 months [t-6,t]	-0.162**	-0.051	0.020	0.012	-0.150***	-0.097**	-0.126***	-0.012	-0.143***	-0.142***
	(-2.06)	(-0.68)	(0.25)	(0.16)	(-3.13)	(-2.23)	(-3.22)	(-0.87)	(-4.24)	(-3.45)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Table 5: Reaction of earnings forecasts to ESG incidents—By E/S/G category (two or more events)

This table reports the results of regressions of changes in EPS consensus forecasts, PTG, and returns 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 months [t-6,t]	-0.058	0.026	-0.171*	-0.074	-0.093	-0.077	-0.077	0.027	-0.053	-0.064
	(-0.57)	(0.28)	(-1.81)	(-0.81)	(-1.60)	(-1.35)	(-1.42)	(1.62)	(-1.55)	(-1.27)
>=2 E incidents in months [t-6,t]	-0.282*	-0.168	-0.255*	-0.300*	-0.120	-0.197**	-0.142*	-0.018	-0.168***	-0.125*
	(-1.92)	(-1.17)	(-1.82)	(-1.97)	(-1.25)	(-2.35)	(-1.70)	(-0.76)	(-3.19)	(-1.94)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

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 months [t-6,t]	-0.096	-0.135*	-0.055	-0.015	-0.138***	-0.155***	-0.151***	0.015	-0.141***	-0.138***
	(-1.29)	(-1.92)	(-0.85)	(-0.22)	(-3.24)	(-3.70)	(-3.90)	(1.20)	(-5.04)	(-3.98)
>=2 S incidents in months [t-6,t]	-0.267***	-0.325***	-0.279***	-0.211**	-0.258***	-0.266***	-0.241***	-0.026*	-0.232***	-0.151***
	(-2.86)	(-3.64)	(-2.94)	(-2.40)	(-4.31)	(-4.94)	(-4.74)	(-1.69)	(-6.09)	(-3.07)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

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 months [t-6,t]	-0.121	-0.004	0.060	0.041	-0.108**	-0.073	-0.127***	-0.003	-0.138***	-0.171***
	(-1.57)	(-0.05)	(0.73)	(0.51)	(-2.20)	(-1.65)	(-3.04)	(-0.21)	(-3.93)	(-4.13)
>=2 G incidents in months [t-6,t]	-0.258**	-0.163	-0.074	-0.056	-0.251***	-0.154**	-0.124**	-0.031*	-0.153***	-0.070
	(-2.02)	(-1.50)	(-0.66)	(-0.59)	(-3.42)	(-2.44)	(-2.26)	(-1.70)	(-3.24)	(-1.06)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Table 6: Reaction of earnings forecasts to ESG incidents, by novelty, severity, and reach

This table reports the results of regressions of changes in EPS consensus forecasts, PTG, and returns on ESG incidents of different levels of novelty, severity and reach. 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 return in month t. In Panel A, the independent variables are two dummy variables equal to one if at least one high- or low-novelty incident occurs in months $[t-6, t]$, respectively. In Panel B, the independent variables are two dummy variables equal to one if at least one high- or low-severity incident occurs in months $[t-6, t]$, respectively. In Panel C, the independent variables are two dummy variables equal to one if at least one high- or low-reach incident occurs in months $[t-6, t]$, respectively. Low-novelty, low-severity and low-reach incidents are RepRisk incidents with novelty, severity and reach level, respectively, equal to one. High-novelty, high-severity and high-reach incidents are RepRisk incidents with novelty, severity and reach levels, respectively, equal to 2 or 3. Standard errors are double clustered at the firm and month levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: High vs. low novelty incidents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	LTG	PTG	Ret.
>=1 low-novelty incidents in months [t-6,t]	-0.167*	-0.104	-0.012	-0.045	-0.121**	-0.079	-0.071	-0.000	-0.086**	-0.071
	(-1.74)	(-1.22)	(-0.14)	(-0.52)	(-2.10)	(-1.49)	(-1.49)	(-0.00)	(-2.53)	(-1.59)
>=1 high-novelty incidents in months [t-6,t]	-0.097	-0.098	-0.089	-0.043	-0.109**	-0.145***	-0.152***	-0.006	-0.164***	-0.152***
	(-1.49)	(-1.41)	(-1.34)	(-0.76)	(-2.61)	(-3.64)	(-3.84)	(-0.52)	(-6.10)	(-4.44)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Panel B: High vs. low severity incidents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	LTG	PTG	Ret.
>=1 low-severity incidents in months [t-6,t]	-0.127**	-0.042	0.007	0.044	-0.025	-0.075*	-0.091***	-0.005	-0.117***	-0.110***
	(-2.01)	(-0.67)	(0.12)	(0.71)	(-0.60)	(-1.97)	(-2.63)	(-0.45)	(-4.49)	(-3.07)
>=1 high-severity incidents in months [t-6,t]	-0.150*	-0.173**	-0.180**	-0.207***	-0.195***	-0.163***	-0.134***	-0.013	-0.144***	-0.108**
	(-1.91)	(-2.24)	(-2.30)	(-2.99)	(-3.88)	(-3.66)	(-3.39)	(-1.05)	(-4.43)	(-2.61)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Panel C: High vs. low reach incidents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	LTG	PTG	Ret.
>=1 low-reach incidents in months [t-6,t]	-0.005	-0.079	-0.062	-0.083	-0.025	-0.010	-0.037	0.017	-0.092***	-0.071*
	(-0.07)	(-1.20)	(-0.94)	(-1.32)	(-0.53)	(-0.23)	(-0.87)	(1.58)	(-3.05)	(-1.74)
>=1 high-reach incidents in months [t-6,t]	-0.208***	-0.108	-0.078	-0.066	-0.151***	-0.184***	-0.159***	-0.017	-0.159***	-0.153***
	(-2.93)	(-1.59)	(-1.21)	(-0.93)	(-3.63)	(-4.69)	(-4.56)	(-1.31)	(-5.69)	(-4.56)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Table 7: Impact of ESG incidents and other incidents on EPS forecasts

This table reports the results of a regression of the changes in consensus EPS forecasts on ESG incidents and negative key development (KD) incidents. In columns (1)-(3), the dependent variables are changes in the 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$. The first independent variable is equal to one if at least one ESG incident happens in months $[t-6, t]$, and zero otherwise. The second independent variable is equal to one if at least one negative KD incident happens in months $[t-6, t]$, and 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 levels. 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
>=1 ESG Incidents in months [t-6,t]	-0.126***	-0.145***	-0.156***	-0.126***	-0.126***
	(-3.03)	(-3.75)	(-4.23)	(-3.04)	(-3.04)
>= 1 KD Negative Incidents in months [t-6,t]	-0.482***	-0.387***	-0.288***	-0.482***	-0.482***
	(-11.26)	(-10.51)	(-8.13)	(-11.35)	(-11.36)
>=1 ESG Incidents in months [t-6,t] × 2-year				-0.019	
				(-0.59)	
>= 1 KD Negative Incidents in months [t-6,t] × 2-year				0.095***	
				(3.39)	
>=1 ESG Incidents in months [t-6,t] × 3-year					-0.030
					(-0.74)
>= 1 KD Negative Incidents in months [t-6,t] × 3-year					0.194***
					(5.21)
$\beta_{ESG \times h-year} - \beta_{KD \times h-year}$				-0.115	-0.224
F-stat				7.049	16.661
P value				0.009	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	0.084	0.100	0.079	0.092	0.082
Obs.	661466	649616	500617	1311082	1162083

Table 8: 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 equal to 1 if at least one incident happens in months $[t-6, t]$, and 0 otherwise. In Panel B, the independent variable is equal to 1 if 1 incident happens in months $[t-6, t]$, 2 if more than 1 incident happen in months $[t-6, t]$, and 0 otherwise. Standard errors are double clustered at the firm and month levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
>=1 incidents in months [t-6,t]	-0.018	-0.035**	-0.037**	-0.019	-0.036***	-0.055***	-0.061***	-0.033*	-0.025	0.008	0.020	-0.027**	-0.028**	-0.013
	(-1.17)	(-2.05)	(-2.28)	(-1.22)	(-3.81)	(-4.75)	(-5.04)	(-1.78)	(-1.35)	(0.41)	(1.26)	(-2.53)	(-2.26)	(-1.04)
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	0.096	0.098	0.096	0.098	0.084	0.097	0.083	0.055	0.046	0.044	0.051	0.055	0.049	0.044
Obs.	287848	257668	229055	132583	635184	622496	480707	133105	121208	106544	62080	348421	337610	222117

Panel B: Splitting by the number of incidents

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
1 incident in months [t-6,t]	-0.006	-0.014	-0.010	-0.013	-0.028***	-0.038***	-0.043***	-0.038**	-0.019	0.018	0.021	-0.030**	-0.026**	-0.000
	(-0.36)	(-0.78)	(-0.63)	(-0.75)	(-2.90)	(-3.23)	(-3.30)	(-2.11)	(-1.03)	(0.88)	(1.29)	(-2.35)	(-1.98)	(-0.02)
>=2 incidents in months [t-6,t]	-0.045**	-0.081***	-0.096***	-0.033	-0.054***	-0.095***	-0.099***	-0.021	-0.039	-0.015	0.019	-0.021	-0.033**	-0.041**
	(-2.04)	(-3.74)	(-4.29)	(-1.60)	(-3.93)	(-5.74)	(-5.88)	(-0.78)	(-1.57)	(-0.61)	(0.80)	(-1.56)	(-2.14)	(-2.38)
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	0.096	0.098	0.096	0.098	0.084	0.097	0.083	0.055	0.046	0.044	0.051	0.055	0.049	0.044
Obs.	287848	257668	229055	132583	635184	622496	480707	133105	121208	106544	62080	348421	337610	222117

Table 9: Event Study: analysts and market reaction after an ESG incident

Thie table reports the results for the event sutdy on how analysts and market reaction after ESG incidents in a month. Specifically, it reports the coefficient β and corresponding t-statisitics of regression $y_{t,t+s} = \alpha + \beta \mathbb{1}\{ESG\ incidents\ in\ month\ t\} + \gamma_{Country \times Industry \times t} + Controls + \epsilon_{i,t}$. Each row indicates one window length s, indicated by the first column. $s = 0$ indicates the contemporaneous month when the incident happens. In column 1 and 2, the dependent variable is the impled value change between $[t, t+s]$ if only changing the EPS forecasts, defined as $\frac{PV(EPS1_{t+s}, EPS2_{t+s}, EPS3_{t+s}) - PV(EPS1_{t-1}, EPS2_{t-1}, EPS3_{t-1})}{PV(EPS1_{t-1}, EPS2_{t-1}, EPS3_{t-1})}$, where $EPS1, EPS2, EPS3$ are one-, two- and three-year ahead forecasts, and PV is the dividend discount model using all the parameters of month $t-1$, defined in Section 5.2 of the paper. In column 3 and 4, the dependent variable is the return between $[t, t+s]$. In column 5 and 6, the dependent variable is the discount rate change between $[t, t+s]$, defined as $\frac{r_{t+s} - r_{t-1}}{r_{t-1}}$, where r_t is the implied discount rate end of month t. Control variables include size and book-to-market ratio quintiles of firms. The coefficients are shown in percentage points. t-statistics are based on standard errors double clustered by firm and by month.

	$\widehat{\Delta PV}/PV$		Return		$\Delta r/r$	
	(1)	(2)	(3)	(4)	(5)	(6)
Window	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
$[t, t]$	-0.08	-1.41	-0.24	-3.51	0.05	2.08
$[t, t+1]$	-0.13	-1.19	-0.32	-2.99	0.06	1.63
$[t, t+2]$	-0.24	-1.63	-0.36	-2.68	0.04	0.79
$[t, t+3]$	-0.41	-2.16	-0.30	-1.84	-0.01	-0.11
$[t, t+4]$	-0.58	-2.49	-0.29	-1.51	-0.03	-0.41
$[t, t+5]$	-0.76	-2.82	-0.23	-1.05	-0.06	-0.94
$[t, t+6]$	-0.86	-2.74	-0.36	-1.45	-0.07	-1.11

Table 10: Variation across regions

This table reports the results of regressions of changes in the consensus EPS and sales forecasts as well as PTG and returns 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 levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: EPS/PTG forecasts and Returns

	(1) 1 year	(2) 2 year	(3) 3 year	(4) LTG	(5) PTG	(6) Return
>=1 incidents in months [t-6,t]	-0.082	-0.126**	-0.233***	-0.009	-0.180***	-0.112*
	(-1.21)	(-2.02)	(-3.73)	(-0.66)	(-3.95)	(-1.82)
>=1 incidents in months [t-6,t] × EU15	-0.080	-0.077	0.101	0.038	-0.042	-0.185*
	(-0.67)	(-0.77)	(1.15)	(1.33)	(-0.54)	(-1.85)
>=1 incidents in months [t-6,t] × Asia	-0.100	-0.042	0.099	0.016	0.011	-0.091
	(-1.06)	(-0.55)	(1.22)	(0.54)	(0.18)	(-1.16)
>=1 incidents in months [t-6,t] × Others	-0.003	0.031	0.173*	0.019	0.103	-0.050
	(-0.03)	(0.26)	(1.80)	(0.40)	(1.25)	(-0.49)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
adj R2	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	661466	649616	500617	226021	645591	638384

Panel B: Sales forecasts

	(1) 1 year	(2) 2 year	(3) 3 year
>=1 incidents in months [t-6,t]	-0.027*	-0.056***	-0.073***
	(-1.78)	(-3.17)	(-3.68)
>=1 incidents in months [t-6,t] × EU15	0.015	-0.008	0.003
	(0.59)	(-0.28)	(0.09)
>=1 incidents in months [t-6,t] × Asia	-0.022	0.011	0.045
	(-1.10)	(0.46)	(1.64)
>=1 incidents in months [t-6,t] × Others	-0.022	-0.010	-0.029
	(-0.73)	(-0.29)	(-0.69)
Month × Industry × Country FE	YES	YES	YES
Firm FE	YES	YES	YES
adj R2	0.084	0.097	0.083
Obs.	635184	622496	480707

Table 11: Interaction with advertising intensity

This table reports the results of regressions of changes in consensus EPS and sales forecasts as well as PTG and returns 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 variable 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 levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: EPS/PTG forecasts and returns

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t-6,t]	-0.087	-0.052	-0.022	-0.086	-0.091	-0.119**	-0.172***	-0.005	-0.144***	-0.162***
	(-0.95)	(-0.57)	(-0.26)	(-1.10)	(-1.58)	(-2.29)	(-3.54)	(-0.33)	(-4.37)	(-3.68)
>=1 incidents in months [t-6,t] × High Ad Intensity	-0.142	-0.180	-0.131	0.092	-0.100	-0.076	0.037	0.017	-0.062	-0.038
	(-1.09)	(-1.41)	(-1.21)	(0.88)	(-1.32)	(-1.13)	(0.63)	(0.74)	(-1.34)	(-0.56)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Panel B: Sales forecasts

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
>=1 incidents in months [t-6,t]	-0.008	-0.016	-0.024	0.006	-0.024**	-0.042***	-0.047***
	(-0.41)	(-0.67)	(-1.03)	(0.27)	(-2.01)	(-2.93)	(-3.06)
>=1 incidents in months [t-6,t] × High Ad Intensity	-0.025	-0.047	-0.031	-0.060*	-0.031*	-0.034*	-0.037
	(-0.84)	(-1.51)	(-0.98)	(-1.94)	(-1.85)	(-1.69)	(-1.62)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.096	0.098	0.096	0.098	0.084	0.097	0.083
Obs.	287848	257668	229055	132583	635184	622496	480707

Table 12: Interaction with firm size

This table reports the results of regressions of changes in consensus EPS and sales forecasts as well as PTG and returns 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 variable 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 levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: EPS/PTG forecasts and returns

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t-6,t]	-0.193	-0.177	-0.197	-0.184*	-0.222***	-0.248***	-0.238***	-0.011	-0.205***	-0.216***
	(-1.65)	(-1.57)	(-1.65)	(-1.69)	(-3.36)	(-4.00)	(-3.63)	(-0.42)	(-5.10)	(-3.84)
>=1 incidents in months [t-6,t] × LargeFirm	0.082	0.086	0.197	0.214*	0.168**	0.180***	0.134*	0.017	0.068	0.066
	(0.59)	(0.68)	(1.46)	(1.74)	(2.36)	(2.77)	(1.90)	(0.61)	(1.52)	(0.90)
LargeFirm	0.670***	0.701***	0.629***	0.575***	0.642***	0.663***	0.616***	0.034	0.549***	-1.422***
	(5.39)	(5.31)	(4.72)	(4.55)	(8.57)	(8.83)	(8.63)	(1.54)	(9.50)	(-12.17)
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	0.090	0.091	0.084	0.094	0.084	0.100	0.079	0.072	0.174	0.374
Obs.	295231	272345	249829	150188	661461	649610	500615	226021	645589	638383

Panel B: Sales forecasts

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
>=1 incidents in months [t-6,t]	-0.020	-0.030	-0.044*	-0.046*	-0.041***	-0.070***	-0.056***
	(-0.87)	(-1.25)	(-1.75)	(-1.82)	(-3.20)	(-3.94)	(-2.94)
>=1 incidents in months [t-6,t] × LargeFirm	0.004	-0.008	0.011	0.042	0.010	0.027	-0.007
	(0.13)	(-0.27)	(0.36)	(1.46)	(0.61)	(1.31)	(-0.31)
LargeFirm	0.100***	0.118***	0.136***	0.053*	0.085***	0.141***	0.166***
	(3.64)	(4.18)	(4.72)	(1.85)	(5.30)	(6.94)	(7.54)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.096	0.099	0.096	0.098	0.084	0.097	0.083
Obs.	287847	257667	229055	132583	635159	622474	480705

Table 13: Impact of ESG incidents on realized earnings, sales, and gross margin

This table reports the results of a regression of realized earnings, sales, and gross margin on ESG incidents. In columns (1)-(3), the dependent variables are the changes in earnings ($\frac{Earnings_{t+h} - Earnings_{t-1}}{abs(Earnings_{t-1})}$) over one-year, two-year and, three-year periods, respectively. In columns (4)-(6), the dependent variables are the changes in sales ($\frac{Sales_{t+h} - Sales_{t-1}}{abs(Sales_{t-1})}$) over one-year, two-year, and, three-year periods, respectively. In columns (7)-(9), the dependent variables are the changes in gross margin ($\frac{GrossMargin_{t+h} - GrossMargin_{t-1}}{abs(GrossMargin_{t-1})}$) over one-year, two-year, and three-year periods, respectively. In Panel A, the independent variable is a dummy variable equal to one if at least one ESG incident happens between the end of year $t-1$ and the end of year t. In Panel B, the independent variables are two dummy variables equal to one if the number of incidents in the year is higher or lower, respectively, than the median of all firms that have any incidents in that year. Standard errors are double clustered at the firm and year levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	Earnings			Sales			GrossMargin		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$
>=1 incidents year [t-1,t]	-0.088***	-0.118***	-0.091***	-0.012***	-0.026***	-0.042***	-0.003	-0.005	-0.002
	(-4.79)	(-4.79)	(-3.17)	(-5.43)	(-6.66)	(-8.06)	(-1.41)	(-1.37)	(-0.38)
Year × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.063	0.101	0.124	0.263	0.336	0.394	0.036	0.087	0.139
Obs.	83420	79549	73309	85293	81247	75107	73582	70077	64519

Panel B: Splitting by the number of incidents

	Earnings			Sales			GrossMargin		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$
lower number of incidents year [t-1,t]	-0.071***	-0.086***	-0.069**	-0.011***	-0.023***	-0.038***	-0.003	-0.002	-0.000
	(-3.65)	(-3.34)	(-2.33)	(-4.60)	(-5.72)	(-7.27)	(-1.30)	(-0.60)	(-0.05)
higher number of incidents year [t-1,t]	-0.145***	-0.233***	-0.179***	-0.017***	-0.037***	-0.057***	-0.004	-0.014**	-0.007
	(-5.20)	(-6.07)	(-3.80)	(-5.06)	(-6.09)	(-6.63)	(-1.01)	(-2.51)	(-1.02)
Year × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.063	0.101	0.124	0.263	0.336	0.394	0.036	0.087	0.139
Obs.	83420	79549	73309	85293	81247	75107	73582	70077	64519

Table 14: Analyst-level forecast revisions and forecast errors

This table reports the results of a regression of changes in analyst-level forecast errors on forecast revisions. The dependent variable is the change in the forecast error from month $t-1$ to month t, defined as $\frac{|FEPS_t - Realized| - |FEPS_{t-1} - Realized|}{|Realized|}$. The independent variables are a dummy variable equal to one if the analyst adjusts her forecast downward in that month for that firm and its interaction with a dummy variable equal to one if at least one incident happens in months $[t-6, t]$. All the regressions control for forecast target (i.e., firm $\times$ earnings announcement) $\times$ month of forecast fixed effects. Standard errors are double clustered at the firm and year levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
Downward Adjustment	-0.005***	-0.012***	-0.015***	-0.012***	-0.014***	-0.022***	-0.024***
	(-6.21)	(-9.92)	(-11.33)	(-9.33)	(-16.77)	(-19.76)	(-21.13)
>=1 incidents in months [t-6,t] × Downward Adjustment	-0.001	-0.002*	-0.002*	-0.003**	-0.002***	-0.003***	-0.004***
	(-0.91)	(-1.83)	(-1.79)	(-2.33)	(-2.84)	(-3.56)	(-3.98)
Firm × Earnings Announcement × Month	YES	YES	YES	YES	YES	YES	YES
adj R2	0.303	0.272	0.263	0.219	0.225	0.214	0.198
Obs.	2656113	2222054	1741710	860246	8693747	7434766	3248309

Table 15: 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	-0.740***	-0.807***	-0.040	-0.019***	-0.026***	-0.001**
	(-6.82)	(-6.21)	(-1.23)	(-5.55)	(-5.34)	(-2.32)
log(num. incidents) in month t-1	-0.736***	-0.791***	-0.087***	-0.019***	-0.024***	-0.002***
	(-6.91)	(-6.78)	(-2.68)	(-5.63)	(-5.76)	(-3.71)
log(num. incidents) in month t-2	-0.664***	-0.778***	-0.063**	-0.017***	-0.025***	-0.002***
	(-6.74)	(-6.99)	(-2.17)	(-5.47)	(-6.41)	(-3.14)
log(num. incidents) in month t-3	-0.679***	-0.800***	-0.053*	-0.018***	-0.023***	-0.001***
	(-6.83)	(-7.70)	(-1.91)	(-5.62)	(-6.15)	(-2.86)
log(num. incidents) in month t-4	-0.627***	-0.807***	-0.047*	-0.017***	-0.023***	-0.001***
	(-6.49)	(-7.95)	(-1.75)	(-5.32)	(-6.15)	(-2.73)
log(num. incidents) in month t-5	-0.615***	-0.855***	-0.068**	-0.017***	-0.025***	-0.001***
	(-6.18)	(-8.79)	(-2.37)	(-5.29)	(-6.90)	(-3.10)
log(num. incidents) in month t-6	-0.601***	-0.867***	-0.074**	-0.017***	-0.025***	-0.002***
	(-6.05)	(-9.10)	(-2.43)	(-5.24)	(-6.84)	(-3.05)
log(num. incidents) in month t-7	-0.635***	-0.850***	-0.064**	-0.019***	-0.024***	-0.001***
	(-6.33)	(-8.85)	(-2.12)	(-5.69)	(-6.52)	(-2.86)
log(num. incidents) in month t-8	-0.669***	-0.911***	-0.078**	-0.020***	-0.027***	-0.002***
	(-6.42)	(-9.20)	(-2.60)	(-5.92)	(-6.97)	(-3.32)
log(num. incidents) in month t-9	-0.750***	-0.953***	-0.079**	-0.022***	-0.027***	-0.002***
	(-6.76)	(-9.45)	(-2.41)	(-6.41)	(-6.75)	(-3.26)
log(num. incidents) in month t-10	-0.769***	-1.018***	-0.076**	-0.023***	-0.030***	-0.002***
	(-6.88)	(-9.45)	(-2.07)	(-6.65)	(-7.13)	(-2.89)
log(num. incidents) in month t-11	-0.859***	-1.075***	-0.105***	-0.026***	-0.031***	-0.002***
	(-7.27)	(-9.55)	(-2.70)	(-7.32)	(-7.15)	(-3.46)
log(num. incidents) in month t-12	-0.906***	-1.167***	-0.147***	-0.028***	-0.032***	-0.003***
	(-7.14)	(-9.31)	(-3.43)	(-7.55)	(-6.67)	(-4.16)
Month * Industry FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Sum of Coef.	-9.250	-11.680	-0.982	-0.261	-0.341	-0.023
F-stat	150.662	95.884	9.443	188.172	64.558	16.778
p-value	0.000	0.000	0.003	0.000	0.000	0.000
Adj. R2	0.889	0.767	0.903	0.867	0.674	0.904
Obs.	325458	281059	184332	325458	281059	184332

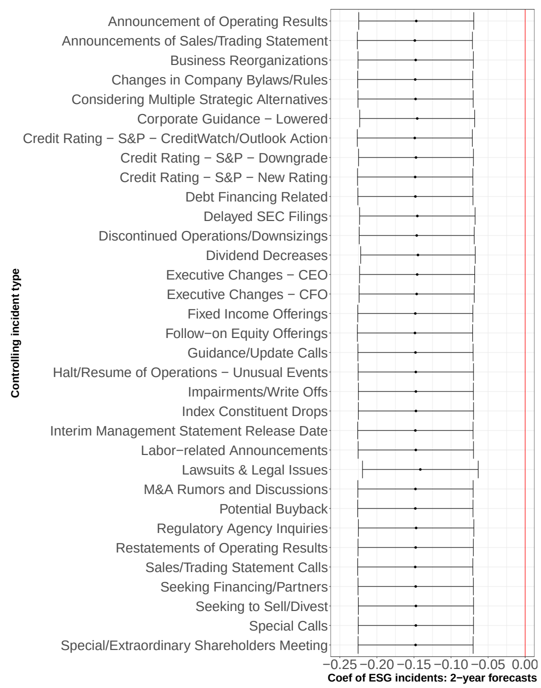
Internet appendix

Figure IA.1: **Impact of ESG incidents on earnings forecasts and stock prices, controlling for one Key Development at a time**

The figure shows the impact of of ESG incidents on analyst forecasts or returns when controlling for each type of Key Development. It reports estimates and 95% confidence intervals of β from the following regression
$$\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1}EPS_{i,t+h})} = \alpha + \beta\,\mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} + \eta\,\mathbb{1}\{KeyDev\ incident\ type\ m\ in\ [t-6,t]\} + \gamma_{Country\times Industry\times t} + \sigma_i + \epsilon_{i,t}$$
where $KeyDev\ incident\ type\ m$ corresponds to the types on the y-axis. Subfigure (a) reports results for 1-year ahead forecasts. Subfigure (b) reports results for 2-year ahead forecasts. Subfigure (c) reports results for 3-year ahead forecasts. Subfigure (d) reports results for returns. Confidence intervals are at 95% level and are based on standard errors double clustered at the firm and month levels.

(a) 1-year forecasts

(b) 2-year forecasts



(c) 3-year forecasts

(d) Return

Table IA.1: Examples

This table lists examples of incidents in RepRisk. Sev, Nov, Rea indicate levels of severity, novelty and reach respectively (labeled by RepRisk).

Firm	Date	Related issues	Sev	Nov	Rea	Summary
JinkoSolar Holding Co., Ltd.	19-Sep-2011	Impacts on communities; Impacts on landscapes, ecosystems and biodiversity; Local pollution; Waste issues	1	2	3	A solar panel factory in Zhejiang province, China, was shut down after local residents protested, claiming the factory's pollution caused a fish die-off in a nearby river. The protests turned violent, with demonstrators damaging the plant. Tests revealed high fluoride levels in the water. The factory's owner, Jinko Solar, admitted to accidental chemical discharge during a rainstorm.
Dunkin' Brands Group Inc	06-Jun-2014	Impacts on communities; Impacts on landscapes, ecosystems and biodiversity; Climate change, GHG emissions, and global pollution; Controversial products and services	1	2	1	Dunkin' Donuts, among other leading doughnut companies, are sourcing palm oil from suppliers who are clear-cutting rain forests and destroying wildlife habitat and carbon-rich peatlands.
Vale S.A.	27-Jan-2019	Impacts on communities; Waste issues; Violation of national legislation; Occupational health and safety issues	3	1	3	A tailings dam in Brazil, owned by the mining company Vale, suffered a catastrophic failure. The collapse of the dam released a mudflow that engulfed the mine's headquarters, including a cafeteria during lunchtime, along with houses, farms, inns, and roads downstream. 270 people died as a result of the collapse.
Suzuki Motor Corp	18-May-2016	Violation of national legislation; Products (health and environmental issues); Fraud	1	2	3	Suzuki Motor Corporation admitted to using improper methods to determine the fuel economy of 16 of its vehicles sold in Japan. It is found to use unapproved testing methods to exaggerate fuel performance.
Wynn Resorts Ltd	27-Jan-2018	Human rights abuses and corporate complicity; Poor employment conditions	1	2	3	Multiple allegations of sexual misconduct were reported against former CEO of Wynn Resorts. Employees claimed the former CEO pressured them into performing sexual acts and created a highly sexualized work environment.
Insys Therapeutics Inc	02-May-2019	Violation of national legislation; Controversial products and services; Corruption, bribery, extortion and money laundering; Fraud	1	1	3	Top executives of Insys Therapeutics, including the founder, were found guilty of racketeering. The executives conspired to boost sales of the fentanyl-based drug by bribing doctors and deceiving insurers.
Lonmin PLC	17-Aug-2012	Human rights abuses and corporate complicity	3	2	2	South Africa's national police shot on striking miners, causing 34 death and 78 wounded during miners' strike calling for increased wages at the Lonmin platinum mine in Rustenburg, South Africa.
Petrofac Ltd	07-Feb-2019	Violation of national legislation; Corruption, bribery, extortion and money laundering	1	2	3	Former global head of sales at Petrofac admitted offering corrupt payments in an attempt to secure contracts in Saudi Arabia worth $3.5bn and contracts in Iraq worth $730m.
Tokyo Electric Power Co Holdings Inc	20-Aug-2013	Local pollution; Occupational health and safety issues; Controversial products and services	2	1	3	A tank at Japan's Fukushima Daiichi Nuclear Power Plant leaked 300 tons of highly contaminated water, prompting fears of environmental damage. The contaminated water, containing dangerous levels of radioactive materials, seeped into the soil and could potentially reach the ocean.
Microsoft Corp	15-Nov-2017	Human rights abuses and corporate complicity; Supply chain issues; Child labor	1	1	3	Microsoft Corp, among other major electronics companies, failed to adequately address child labor and human rights abuses in their cobalt supply chains from the Democratic Republic of Congo (DRC). Miners in the DRC, including children, often work in extremely dangerous and exploitative conditions.

Table IA.2: 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	3,254,955	39.73	1,623,875	28.27	1,631,080	66.58
JPN	578,774	7.06	492,361	8.57	86,413	3.53
CHN	537,275	6.56	516,901	9.00	20,374	0.83
KOR	349,563	4.27	223,208	3.89	126,355	5.16
CAN	335,410	4.09	198,717	3.46	136,693	5.58
GBR	281,633	3.44	274,294	4.78	7,339	0.30
IND	249,221	3.04	224,733	3.91	24,488	1.00
TWN	218,623	2.67	114,596	2.00	104,027	4.25
AUS	191,532	2.34	191,334	3.33	198	0.01
DEU	173,406	2.12	142,390	2.48	31,016	1.27
FRA	156,415	1.91	147,993	2.58	8,422	0.34
BRA	140,427	1.71	102,056	1.78	38,371	1.57
CYM	115,095	1.40	106,877	1.86	8,218	0.34
SWE	114,881	1.40	72,412	1.26	42,469	1.73
CHE	95,773	1.17	85,510	1.49	10,263	0.42
MYS	90,307	1.10	87,759	1.53	2,548	0.10
NOR	88,389	1.08	56,094	0.98	32,295	1.32
FIN	88,085	1.08	54,614	0.95	33,471	1.37
ESP	73,269	0.89	66,208	1.15	7,061	0.29
ITA	72,621	0.89	67,039	1.17	5,582	0.23
HKG	69,653	0.85	67,307	1.17	2,346	0.10
ZAF	67,969	0.83	66,572	1.16	1,397	0.06
NLD	67,422	0.82	58,118	1.01	9,304	0.38
IDN	66,629	0.81	63,260	1.10	3,369	0.14
BMU	61,883	0.76	58,823	1.02	3,060	0.12
THA	61,880	0.76	57,262	1.00	4,618	0.19
MEX	56,505	0.69	40,530	0.71	15,975	0.65
DNK	51,316	0.63	35,352	0.62	15,964	0.65
SGP	48,575	0.59	44,822	0.78	3,753	0.15
PHL	43,961	0.54	41,392	0.72	2,569	0.10
TUR	43,065	0.53	38,327	0.67	4,738	0.19
POL	39,631	0.48	37,618	0.65	2,013	0.08
BEL	33,962	0.41	31,221	0.54	2,741	0.11
RUS	32,435	0.40	31,861	0.55	574	0.02
AUT	29,276	0.36	25,074	0.44	4,202	0.17
NZL	24,413	0.30	24,413	0.43	0	0.00
CHL	24,081	0.29	19,839	0.35	4,242	0.17
ISR	21,154	0.26	16,914	0.29	4,240	0.17
NGA	19,235	0.23	19,212	0.33	23	0.00
PRT	19,206	0.23	17,591	0.31	1,615	0.07
PAK	17,414	0.21	17,206	0.30	208	0.01
GRC	15,868	0.19	14,793	0.26	1,075	0.04
IRL	15,816	0.19	14,629	0.25	1,187	0.05
LUX	15,751	0.19	12,889	0.22	2,862	0.12
EGY	14,607	0.18	14,462	0.25	145	0.01
KEN	8,531	0.10	8,531	0.15	0	0.00
COL	6,929	0.08	6,115	0.11	814	0.03
ARG	6,217	0.08	6,066	0.11	151	0.01
VNM	4,526	0.06	4,526	0.08	0	0.00

Table IA.3: Reaction of earnings forecasts to ESG incidents—Different lags

This table reports the results of regressions of changes in EPS consensus forecasts, PTG, and returns 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 equal to one if at least one incident happens in months $[t-3, t]$, and 0 otherwise. In Panel B, the independent variable is equal to 1 if at least one incident happens in months $[t-9, t]$, and 0 otherwise. In Panel C, the independent variable is equal to 1 if at least one incident happens in months $[t-12, t]$, and 0 otherwise. Standard errors are double clustered at the firm and month levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Incidents with a 3-month lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t-3,t]	-0.102	-0.135**	-0.062	0.019	-0.137***	-0.130***	-0.155***	-0.009	-0.146***	-0.194***
	(-1.44)	(-2.19)	(-1.00)	(0.29)	(-3.35)	(-3.35)	(-4.02)	(-0.76)	(-5.75)	(-4.99)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Panel B: Incidents with a 9-month lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t-9,t]	-0.089	-0.109*	-0.054	-0.038	-0.148***	-0.159***	-0.180***	-0.006	-0.158***	-0.193***
	(-1.28)	(-1.69)	(-0.78)	(-0.60)	(-3.71)	(-4.15)	(-4.93)	(-0.52)	(-5.67)	(-5.35)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Panel C: Incidents with a 12-month lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t-12,t]	-0.054	-0.121*	-0.023	-0.005	-0.150***	-0.161***	-0.187***	-0.005	-0.167***	-0.187***
	(-0.77)	(-1.83)	(-0.32)	(-0.08)	(-3.61)	(-4.17)	(-5.04)	(-0.46)	(-6.09)	(-4.97)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Table IA.4: Reaction of earnings forecasts to ESG incidents—alternative fixed effects

This table reports the results of a regression of changes in consensus EPS forecasts on recent ESG incidents. The dependent variables are changes in 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 Panel A, the main independent variable is equal to one if at least one incident happens in months $[t-6, t]$, and zero otherwise. In Panel B, the independent variable is equal to one if one incident happens in months $[t-6, t]$, two if more than one incident happen in months $[t-6, t]$, and zero otherwise. Standard errors are double clustered at the firm and month levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1 year	2 year	3 year	1 year	2 year	3 year	1 year	2 year	3 year
>=1 incidents in months [t-6,t]	-0.161***	-0.188***	-0.176***	-0.160***	-0.171***	-0.162***	-0.176***	-0.190***	-0.180***
	(-3.94)	(-5.12)	(-4.76)	(-3.91)	(-4.64)	(-4.58)	(-4.23)	(-5.02)	(-4.85)
Month × Country FE	YES	YES	YES	NO	NO	NO	NO	NO	NO
Month × Industry FE	NO	NO	NO	YES	YES	YES	NO	NO	NO
Month FE	NO	NO	NO	NO	NO	NO	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.063	0.073	0.060	0.063	0.079	0.065	0.052	0.059	0.049
Obs.	690241	678462	529552	690284	678508	529631	690284	678508	529631

Panel B: Splitting by the number of incidents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1 year	2 year	3 year	1 year	2 year	3 year	1 year	2 year	3 year
1 incident in months [t-6,t]	-0.113***	-0.124***	-0.120***	-0.116***	-0.118***	-0.115***	-0.125***	-0.125***	-0.121***
	(-2.76)	(-3.32)	(-3.18)	(-2.83)	(-3.17)	(-3.10)	(-3.00)	(-3.26)	(-3.19)
>=2 incidents in months [t-6,t]	-0.268***	-0.329***	-0.292***	-0.257***	-0.286***	-0.256***	-0.286***	-0.330***	-0.297***
	(-4.55)	(-6.46)	(-5.97)	(-4.36)	(-5.54)	(-5.56)	(-4.75)	(-6.27)	(-6.08)
Month × Country FE	YES	YES	YES	NO	NO	NO	NO	NO	NO
Month × Industry FE	NO	NO	NO	YES	YES	YES	NO	NO	NO
Month FE	NO	NO	NO	NO	NO	NO	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.063	0.073	0.060	0.063	0.079	0.065	0.052	0.059	0.049
Obs.	690241	678462	529552	690284	678508	529631	690284	678508	529631

Table IA.5: Reaction of earnings forecasts to ESG incidents—Time-varying controls without firm fixed effects

This table reports the results of regressions of changes in EPS consensus forecasts, PTG, and returns 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 equal to 1 if at least one incident happens in months $[t-6, t]$, and 0 otherwise. In Panel B, the independent variable is equal to as 1 if 1 incident happens in months $[t-6, t]$, 2 if more than 1 incident happen in months $[t-6, t]$, and 0 otherwise. $Quintile\ MarketCap$ are the market capitalization quintiles calculated based on market capitalization as of IBES consensus date in month $t-1$. $Quintile\ B/M\ Ratio$ are the book-to-market ratio quintiles calculated based on book-to-market ratio as of IBES consensus date in month $t-1$. Standard errors are double clustered at the firm and month levels. 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 months [t-6,t]	-0.392***	-0.219***	-0.141**	-0.135**	-0.287***	-0.217***	-0.205***	-0.008	-0.209***	-0.169***
	(-6.26)	(-3.66)	(-2.48)	(-2.32)	(-7.31)	(-6.10)	(-6.16)	(-0.90)	(-9.02)	(-4.24)
Quintile MarketCap=2	0.460***	0.469***	0.403***	0.027	0.533***	0.485***	0.416***	0.068***	0.394***	0.284***
	(3.71)	(4.05)	(3.76)	(0.29)	(7.85)	(7.80)	(6.27)	(3.41)	(10.52)	(3.67)
Quintile MarketCap=3	0.892***	0.841***	0.757***	0.246**	0.840***	0.762***	0.690***	0.073***	0.498***	0.347***
	(6.44)	(6.99)	(6.74)	(2.36)	(11.66)	(11.43)	(9.57)	(3.76)	(11.12)	(3.43)
Quintile MarketCap=4	1.351***	1.208***	1.005***	0.370***	1.124***	0.932***	0.835***	0.101***	0.567***	0.330***
	(8.80)	(9.04)	(8.47)	(3.58)	(14.30)	(12.67)	(10.87)	(5.10)	(10.69)	(2.85)
Quintile MarketCap=5	1.764***	1.518***	1.168***	0.422***	1.409***	1.134***	1.031***	0.116***	0.624***	0.359**
	(10.16)	(10.46)	(9.10)	(3.49)	(15.49)	(13.19)	(11.86)	(5.37)	(10.93)	(2.59)
Quintile B/M Ratio=2	-0.180**	-0.019	0.052	0.056	-0.115**	-0.110**	-0.056	-0.003	-0.379***	-0.028
	(-2.24)	(-0.26)	(0.81)	(0.99)	(-2.58)	(-2.46)	(-1.34)	(-0.28)	(-11.32)	(-0.51)
Quintile B/M Ratio=3	-0.737***	-0.486***	-0.266***	-0.160**	-0.401***	-0.401***	-0.243***	-0.002	-0.673***	-0.095
	(-6.80)	(-5.28)	(-3.33)	(-2.46)	(-6.65)	(-7.04)	(-4.69)	(-0.14)	(-14.56)	(-1.14)
Quintile B/M Ratio=4	-1.409***	-1.033***	-0.839***	-0.551***	-0.962***	-0.892***	-0.627***	-0.024*	-0.994***	-0.010
	(-11.18)	(-9.13)	(-7.71)	(-5.99)	(-12.67)	(-11.52)	(-9.38)	(-1.70)	(-17.24)	(-0.09)
Quintile B/M Ratio=5	-1.996***	-1.817***	-1.622***	-1.175***	-1.811***	-1.687***	-1.308***	-0.046**	-1.466***	-0.089
	(-11.99)	(-12.07)	(-11.18)	(-9.17)	(-17.17)	(-15.71)	(-13.80)	(-2.53)	(-19.14)	(-0.50)
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	0.070	0.078	0.075	0.082	0.065	0.086	0.070	0.077	0.172	0.371
Obs.	293625	270839	248466	149583	657651	645913	498722	225522	641461	634912

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in months [t-6,t]	-0.233***	-0.112*	-0.036	-0.098*	-0.213***	-0.179***	-0.164***	-0.000	-0.171***	-0.178***
	(-3.50)	(-1.71)	(-0.60)	(-1.66)	(-5.38)	(-4.85)	(-4.47)	(-0.02)	(-7.23)	(-4.83)
>=2 incidents in months [t-6,t]	-0.566***	-0.335***	-0.255***	-0.174**	-0.373***	-0.262***	-0.250***	-0.016	-0.255***	-0.158***
	(-6.61)	(-4.21)	(-3.41)	(-2.20)	(-6.79)	(-5.32)	(-5.80)	(-1.56)	(-7.95)	(-2.85)
Quintile MarketCap=2	0.467***	0.473***	0.408***	0.029	0.538***	0.488***	0.418***	0.069***	0.396***	0.283***
	(3.78)	(4.10)	(3.80)	(0.31)	(7.91)	(7.85)	(6.30)	(3.44)	(10.55)	(3.68)
Quintile MarketCap=3	0.904***	0.849***	0.765***	0.249**	0.847***	0.766***	0.694***	0.073***	0.502***	0.346***
	(6.55)	(7.09)	(6.82)	(2.38)	(11.75)	(11.53)	(9.61)	(3.78)	(11.18)	(3.44)
Quintile MarketCap=4	1.377***	1.225***	1.021***	0.376***	1.137***	0.939***	0.843***	0.102***	0.575***	0.328***
	(9.00)	(9.22)	(8.62)	(3.62)	(14.44)	(12.80)	(10.93)	(5.17)	(10.76)	(2.85)
Quintile MarketCap=5	1.849***	1.575***	1.224***	0.441***	1.448***	1.154***	1.052***	0.120***	0.644***	0.355**
	(10.77)	(10.95)	(9.46)	(3.64)	(15.79)	(13.41)	(12.06)	(5.62)	(11.04)	(2.59)
Quintile B/M Ratio=2	-0.177**	-0.017	0.054	0.057	-0.113**	-0.109**	-0.055	-0.002	-0.378***	-0.028
	(-2.19)	(-0.23)	(0.84)	(1.00)	(-2.53)	(-2.43)	(-1.31)	(-0.25)	(-11.29)	(-0.52)
Quintile B/M Ratio=3	-0.725***	-0.479***	-0.258***	-0.158**	-0.396***	-0.398***	-0.240***	-0.001	-0.671***	-0.096
	(-6.68)	(-5.20)	(-3.24)	(-2.42)	(-6.56)	(-6.97)	(-4.64)	(-0.07)	(-14.53)	(-1.15)
Quintile B/M Ratio=4	-1.390***	-1.020***	-0.827***	-0.547***	-0.954***	-0.888***	-0.622***	-0.023	-0.989***	-0.011
	(-11.01)	(-8.98)	(-7.58)	(-5.96)	(-12.53)	(-11.41)	(-9.31)	(-1.61)	(-17.21)	(-0.10)
Quintile B/M Ratio=5	-1.963***	-1.795***	-1.601***	-1.168***	-1.795***	-1.679***	-1.300***	-0.045**	-1.457***	-0.091
	(-11.80)	(-11.93)	(-11.01)	(-9.08)	(-16.94)	(-15.54)	(-13.70)	(-2.43)	(-19.09)	(-0.52)
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	0.070	0.078	0.075	0.082	0.065	0.086	0.070	0.077	0.172	0.371
Obs.	293625	270839	248466	149583	657651	645913	498722	225522	641461	634912

Table IA.6: Reaction of earnings forecasts to ESG incidents—Time-varying controls

This table reports the results of regressions of changes in EPS consensus forecasts, PTG, and returns 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 equal to 1 if at least one incident happens in months $[t-6, t]$, and 0 otherwise. In Panel B, the independent variable is equal to 1 if 1 incident happens in months $[t-6, t]$, 2 if more than 1 incident happen in months $[t-6, t]$, and 0 otherwise. *Quintile MarketCap* are the market capitalization quintiles calculated based on market capitalization as of IBES consensus date in month $t-1$. *Quintile B/M Ratio* are the book-to-market ratio quintiles calculated based on book-to-market ratio as of IBES consensus date in month $t-1$. Standard errors are double clustered at the firm and month levels. 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 months [t-6,t]	-0.112*	-0.097	-0.051	-0.032	-0.100**	-0.119***	-0.136***	0.002	-0.144***	-0.189***
	(-1.71)	(-1.51)	(-0.82)	(-0.55)	(-2.46)	(-3.14)	(-3.76)	(0.15)	(-5.60)	(-5.51)
Quintile MarketCap=2	-0.066	-0.073	-0.052	-0.202	0.109	0.137	0.186*	0.059	0.253***	-1.142***
	(-0.39)	(-0.45)	(-0.34)	(-1.51)	(1.21)	(1.61)	(1.91)	(1.51)	(5.19)	(-11.35)
Quintile MarketCap=3	-0.019	-0.122	0.108	-0.118	0.306**	0.353***	0.440***	0.058	0.368***	-2.199***
	(-0.09)	(-0.59)	(0.53)	(-0.62)	(2.56)	(3.12)	(3.46)	(1.31)	(4.75)	(-13.87)
Quintile MarketCap=4	0.200	0.116	0.277	-0.004	0.519***	0.460***	0.590***	0.096*	0.482***	-3.275***
	(0.80)	(0.45)	(1.12)	(-0.02)	(3.47)	(3.27)	(4.02)	(1.91)	(4.56)	(-14.90)
Quintile MarketCap=5	0.611**	0.492*	0.613**	0.262	0.794***	0.760***	0.835***	0.101*	0.651***	-4.347***
	(2.10)	(1.72)	(2.19)	(1.14)	(4.43)	(4.37)	(5.22)	(1.73)	(4.50)	(-14.50)
Quintile B/M Ratio=2	-0.590***	-0.539***	-0.453***	-0.311***	-0.634***	-0.669***	-0.513***	-0.020	-0.740***	0.310***
	(-5.78)	(-5.76)	(-5.20)	(-3.98)	(-10.87)	(-11.18)	(-10.07)	(-1.32)	(-16.44)	(4.04)
Quintile B/M Ratio=3	-1.381***	-1.300***	-1.082***	-0.831***	-1.254***	-1.340***	-1.028***	-0.029	-1.306***	0.595***
	(-9.05)	(-9.17)	(-8.51)	(-7.41)	(-13.78)	(-15.31)	(-13.97)	(-1.45)	(-19.88)	(4.77)
Quintile B/M Ratio=4	-2.365***	-2.194***	-1.948***	-1.529***	-2.206***	-2.206***	-1.712***	-0.057**	-1.877***	1.008***
	(-12.94)	(-12.51)	(-11.09)	(-10.29)	(-18.80)	(-19.19)	(-17.62)	(-2.15)	(-22.27)	(5.87)
Quintile B/M Ratio=5	-3.435***	-3.342***	-3.103***	-2.494***	-3.577***	-3.475***	-2.717***	-0.077**	-2.623***	1.442***
	(-14.36)	(-14.36)	(-13.02)	(-11.63)	(-22.40)	(-23.43)	(-21.51)	(-2.13)	(-24.79)	(6.22)
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	0.094	0.096	0.089	0.098	0.091	0.107	0.084	0.072	0.180	0.378
Obs.	293494	270761	248378	149328	657581	645854	498586	225397	641415	634869

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in months [t-6,t]	-0.071	-0.054	0.009	-0.014	-0.077*	-0.095**	-0.111***	0.012	-0.118***	-0.165***
	(-1.02)	(-0.79)	(0.14)	(-0.23)	(-1.85)	(-2.44)	(-2.97)	(0.90)	(-4.50)	(-4.81)
>=2 incidents in months [t-6,t]	-0.205**	-0.193**	-0.185**	-0.072	-0.153***	-0.172***	-0.192***	-0.018	-0.204***	-0.243***
	(-2.29)	(-2.18)	(-2.07)	(-0.81)	(-2.66)	(-3.29)	(-3.73)	(-1.20)	(-5.56)	(-4.81)
Quintile MarketCap=2	-0.066	-0.074	-0.051	-0.202	0.109	0.137	0.186*	0.059	0.253***	-1.142***
	(-0.39)	(-0.45)	(-0.34)	(-1.51)	(1.21)	(1.61)	(1.91)	(1.51)	(5.20)	(-11.35)
Quintile MarketCap=3	-0.021	-0.123	0.105	-0.119	0.306**	0.353***	0.441***	0.057	0.368***	-2.199***
	(-0.10)	(-0.60)	(0.52)	(-0.62)	(2.56)	(3.11)	(3.46)	(1.29)	(4.74)	(-13.87)
Quintile MarketCap=4	0.197	0.113	0.272	-0.006	0.518***	0.458***	0.589***	0.095*	0.481***	-3.276***
	(0.79)	(0.44)	(1.10)	(-0.03)	(3.46)	(3.26)	(4.02)	(1.88)	(4.55)	(-14.91)
Quintile MarketCap=5	0.607**	0.488*	0.607**	0.259	0.792***	0.758***	0.832***	0.100*	0.649***	-4.349***
	(2.09)	(1.71)	(2.17)	(1.12)	(4.42)	(4.36)	(5.21)	(1.70)	(4.49)	(-14.51)
Quintile B/M Ratio=2	-0.589***	-0.538***	-0.453***	-0.311***	-0.633***	-0.669***	-0.512***	-0.020	-0.740***	0.310***
	(-5.77)	(-5.76)	(-5.20)	(-3.97)	(-10.86)	(-11.18)	(-10.06)	(-1.30)	(-16.45)	(4.05)
Quintile B/M Ratio=3	-1.380***	-1.299***	-1.080***	-0.831***	-1.253***	-1.340***	-1.028***	-0.029	-1.305***	0.596***
	(-9.04)	(-9.17)	(-8.51)	(-7.41)	(-13.78)	(-15.31)	(-13.97)	(-1.44)	(-19.88)	(4.78)
Quintile B/M Ratio=4	-2.363***	-2.192***	-1.946***	-1.528***	-2.206***	-2.206***	-1.712***	-0.056**	-1.876***	1.009***
	(-12.93)	(-12.50)	(-11.08)	(-10.29)	(-18.80)	(-19.18)	(-17.61)	(-2.14)	(-22.27)	(5.88)
Quintile B/M Ratio=5	-3.434***	-3.340***	-3.102***	-2.494***	-3.576***	-3.474***	-2.716***	-0.077**	-2.622***	1.443***
	(-14.37)	(-14.36)	(-13.03)	(-11.63)	(-22.39)	(-23.42)	(-21.51)	(-2.12)	(-24.78)	(6.22)
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	0.094	0.096	0.089	0.098	0.091	0.107	0.084	0.072	0.180	0.378
Obs.	293494	270761	248378	149328	657581	645854	498586	225397	641415	634869

Table IA.7: Reaction of earnings forecasts to ESG incidents—Controlling for fundamentals

This table reports the results of a regression of the changes in consensus forecasts and returns 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 equal to 1 if at least one incident happens in months $[t-6, t]$, and 0 otherwise. In Panel B, the independent variable is equal to 1 if 1 incident happens in months $[t-6, t]$, 2 if more than 1 incident happen in months $[t-6, t]$, and 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 $\Delta(\frac{NetDebt}{Asset})_t = (\frac{NetDebt}{Asset})_t - (\frac{NetDebt}{Asset})_{t-1}$. ROA_t, $(\frac{Capx}{Asset})_t$ and $(\frac{NetDebt}{Asset})_t$ are based on the latest observable annual balance sheet information as of the IBES consensus date in month t. Standard errors are double clustered at the firm and month levels. 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 months [t-6,t]	-0.161**	-0.107	-0.062	-0.063	-0.108**	-0.146***	-0.160***	-0.007	-0.165***	-0.160***
	(-2.28)	(-1.53)	(-0.93)	(-1.05)	(-2.37)	(-3.46)	(-4.01)	(-0.50)	(-5.86)	(-4.42)
Δ ROA	1.802***	1.505***	1.241***	1.635***	1.751***	1.394***	0.875***	-0.561***	0.688***	0.694***
	(9.17)	(8.59)	(7.17)	(3.22)	(15.58)	(13.89)	(6.04)	(-10.26)	(10.25)	(8.50)
Δ CapEx/Asset	0.043	0.191	0.260	0.169	0.169	0.131	0.368	0.029	-0.310***	-0.302***
	(0.13)	(0.80)	(1.04)	(0.20)	(1.37)	(1.03)	(1.60)	(0.49)	(-3.47)	(-2.85)
Δ NetDebt/Asset	-0.181***	-0.121**	-0.045	0.016	-0.103***	-0.096***	-0.098*	-0.015	-0.105***	-0.115***
	(-3.03)	(-2.50)	(-0.87)	(0.08)	(-3.51)	(-3.02)	(-1.70)	(-1.42)	(-4.69)	(-4.06)
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	0.092	0.096	0.088	0.096	0.086	0.102	0.078	0.071	0.164	0.354
Obs.	269829	249770	230120	139719	568032	557592	427451	194405	549999	543515

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in months [t-6,t]	-0.103	-0.060	0.005	-0.034	-0.069	-0.104**	-0.120***	0.004	-0.128***	-0.153***
	(-1.41)	(-0.81)	(0.07)	(-0.54)	(-1.49)	(-2.43)	(-2.94)	(0.26)	(-4.51)	(-4.27)
>=2 incidents in months [t-6,t]	-0.288***	-0.213**	-0.209**	-0.129	-0.196***	-0.244***	-0.245***	-0.028	-0.251***	-0.177***
	(-3.03)	(-2.26)	(-2.22)	(-1.40)	(-3.09)	(-4.11)	(-4.39)	(-1.63)	(-6.19)	(-3.21)
Δ ROA	1.802***	1.505***	1.241***	1.634***	1.751***	1.394***	0.875***	-0.561***	0.687***	0.694***
	(9.17)	(8.59)	(7.17)	(3.22)	(15.58)	(13.89)	(6.04)	(-10.26)	(10.24)	(8.50)
Δ CapEx/Asset	0.042	0.190	0.259	0.168	0.169	0.131	0.369	0.029	-0.310***	-0.302***
	(0.13)	(0.80)	(1.04)	(0.20)	(1.37)	(1.03)	(1.60)	(0.49)	(-3.47)	(-2.84)
Δ NetDebt/Asset	-0.181***	-0.121**	-0.045	0.016	-0.103***	-0.096***	-0.098*	-0.015	-0.105***	-0.115***
	(-3.03)	(-2.50)	(-0.86)	(0.08)	(-3.51)	(-3.01)	(-1.70)	(-1.42)	(-4.69)	(-4.06)
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	0.092	0.096	0.088	0.096	0.086	0.102	0.078	0.071	0.164	0.354
Obs.	269829	249770	230120	139719	568032	557592	427451	194405	549999	543515

Table IA.8: Reaction of earnings forecasts to ESG incidents - scaled by book value per share

This table reports the results of a regression of changes in consensus EPS forecasts on recent ESG incidents. In columns (1)-(7), the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{Book\ Value\ per\ share} \times 100$, where h is the horizon of the forecasts and the denominator is the book value per share in the previous year. In Panel A, the independent variable is a dummy variable equal to one if at least one incident happens in months $[t-6, t]$ and zero otherwise. In Panel B, the independent variables are two dummy variables equal to one if one incident happens in months $[t-6, t]$ and at least two incidents happen in months $[t-6, t]$, respectively. Standard errors are double clustered at the firm and month levels. 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
>=1 incidents in months [t-6,t]	-0.011**	-0.010**	-0.003	-0.010*	-0.020***	-0.027***	-0.031***
	(-2.14)	(-2.08)	(-0.66)	(-1.86)	(-3.33)	(-4.26)	(-4.60)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.052	0.042	0.040	0.039	0.075	0.093	0.072
Obs.	262608	242564	223236	134426	589371	582043	467440

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
1 incident in months [t-6,t]	-0.008	-0.007	0.002	-0.009*	-0.015**	-0.021***	-0.023***
	(-1.33)	(-1.41)	(0.34)	(-1.67)	(-2.45)	(-3.32)	(-3.38)
>=2 incidents in months [t-6,t]	-0.018***	-0.016**	-0.012**	-0.011	-0.032***	-0.039***	-0.050***
	(-2.78)	(-2.57)	(-2.00)	(-1.56)	(-3.82)	(-4.52)	(-5.03)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.052	0.042	0.040	0.039	0.075	0.093	0.072
Obs.	262608	242564	223236	134426	589371	582043	467440

Table IA.9: Impact on earnings forecasts by type of negative event

This table reports the impact of different types of negative events on earnings forecasts across the 1- to 3-year horizons. For each event type u and horizon h, we estimate the regression equation $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta \mathbb{1}\{type\ u\ incidents\ in\ [t-6,t]\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$, where the dependent variable is the change in the EPS forecasts scaled by the lagged absolute value of the EPS forecasts. The independent variable is equal to one if an event of type u happens in months $[t-6,t]$, and 0 otherwise. The numbers in the table are the estimated βs for each type of event u and forecast horizon h. Results are in %.

Event	1-year horizon	2-year horizon	3-year horizon
ESG Incidents	-0.13	-0.15	-0.16
Announcement of Operating Results	-0.22	-0.22	-0.25
Announcements of Sales/Trading Statement	-0.11	-0.16	-0.09
Business Reorganizations	-0.28	-0.19	-0.17
Changes in Company By laws/Rules	-0.11	-0.05	-0.01
Considering Multiple Strategic Alternatives	-0.84	-0.79	-0.36
Corporate Guidance - Lowered	-2.02	-1.71	-1.33
Credit Rating - CreditWatch/Outlook Action	-0.42	-0.38	-0.24
Credit Rating - Downgrade	-1.46	-1.41	-0.84
Credit Rating - New Rating	-0.28	-0.26	-0.01
Debt Financing Related	-0.12	-0.02	0.00
Delayed SEC Filings	-1.00	-1.03	-0.73
Discontinued Operations/Downsizings	-0.58	-0.50	-0.37
Dividend Decreases	-0.93	-0.81	-0.46
Executive Changes - CEO	-0.48	-0.38	-0.32
Executive Changes - CFO	-0.31	-0.33	-0.24
Fixed Income Offerings	-0.23	-0.11	-0.05
Follow-on Equity Offerings	-0.18	-0.22	-0.26
Guidance/Update Calls	-1.04	-1.02	-0.75
Halt/Resume of Operations	-0.84	-0.69	-0.42
Impairments/Write Offs	-0.36	-0.24	-0.05
Index Constituent Drops	-0.20	-0.21	-0.15
Interim Management Statement Release	-0.33	-0.36	-0.16
Labor-related Announcements	-0.27	-0.22	-0.11
Legal Issues	-0.30	-0.23	-0.19
M&A Rumors and Discussions	-0.27	-0.22	-0.23
Potential Buyback	-0.18	0.04	-0.02
Regulatory Agency Inquiries	-0.38	-0.40	-0.32
Restatements of Operating Results	-0.48	-0.23	-0.12
Sales/Trading Statement Calls	-0.31	-0.46	-0.42
Seeking Financing/Partners	-0.21	-0.21	-0.02
Seeking to Sell/Divest	-0.22	-0.31	-0.26
Special Calls	-0.21	-0.14	-0.14
Special Shareholders Meeting	-0.15	-0.08	-0.03

Table IA.10: Reaction of earnings forecasts to ESG incidents - controlling for all KD incidents

This table reports the results of a regression of changes in consensus EPS forecasts on recent ESG incidents, controlling for Key Development 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 is equal to one if at least one incident happens in months $[t-6, t]$, and zero otherwise. In Panel B, the independent variable is equal to one if one incident happens in months $[t-6, t]$, two if more than one incident happen in months $[t-6, t]$, and zero otherwise. Standard errors are double clustered at the firm and month levels. All the regressions include 33 dummy variables indicating whether Key Development incidents happen in months $[t-6, t]$. 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) PTG	(9) Ret.
>=1 ESG Incidents in months [t-6,t]	-0.121*	-0.103	-0.058	-0.039	-0.107***	-0.129***	-0.144***	-0.157***	-0.168***
	(-1.86)	(-1.60)	(-0.91)	(-0.68)	(-2.62)	(-3.38)	(-3.95)	(-5.94)	(-4.98)
KeyDev Incidents Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.094	0.094	0.086	0.095	0.088	0.103	0.081	0.175	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	645591	638384

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) PTG	(9) Ret.
1 ESG Incident in months [t-6,t]	-0.059	-0.046	0.016	-0.010	-0.070*	-0.094**	-0.109***	-0.122***	-0.160***
	(-0.85)	(-0.67)	(0.25)	(-0.16)	(-1.69)	(-2.39)	(-2.89)	(-4.60)	(-4.71)
>=2 ESG Incidents in months [t-6,t]	-0.259***	-0.230***	-0.223**	-0.105	-0.192***	-0.211***	-0.220***	-0.236***	-0.187***
	(-2.96)	(-2.66)	(-2.47)	(-1.21)	(-3.30)	(-4.02)	(-4.31)	(-6.28)	(-3.84)
KeyDev Incidents Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.094	0.094	0.086	0.095	0.088	0.104	0.081	0.175	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	645591	638384

Table IA.11: Reaction of sales forecasts to ESG incidents - forecast revisions scaled by book value

This table reports the results of a regression of changes in consensus sales forecasts on recent ESG incidents. In columns (1)-(7), the dependent variables are changes in the 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizon sales forecasts, defined as $\frac{F_t Sales_{t+h} - F_{t-1} Sales_{t+h}}{Book\ Value} \times 100$, where h is the horizon of the forecasts and the denominator is the book value at the end of the previous year. In Panel A, the independent variable is a dummy variable equal to one if at least one incident happens in months $[t-6, t]$ and zero otherwise. In Panel B, the independent variables are two dummy variables equal to one if one incident happens in months $[t-6, t]$ and if at least two incidents happen in months $[t-6, t]$, respectively. Standard errors are double clustered at the firm and month levels. 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
>=1 incidents in months [t-6,t]	-0.032*	-0.029	-0.028	-0.014	-0.063***	-0.111***	-0.130***
	(-1.74)	(-1.52)	(-1.44)	(-0.80)	(-2.80)	(-4.24)	(-4.37)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.069	0.059	0.055	0.063	0.085	0.098	0.083
Obs.	253868	227214	202351	117170	561609	553651	443884

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
1 incident in months [t-6,t]	-0.026	-0.014	-0.014	-0.012	-0.052**	-0.084***	-0.104***
	(-1.37)	(-0.71)	(-0.68)	(-0.61)	(-2.33)	(-3.20)	(-3.28)
>=2 incidents in months [t-6,t]	-0.047*	-0.061**	-0.058**	-0.018	-0.088***	-0.172***	-0.187***
	(-1.85)	(-2.46)	(-2.42)	(-0.86)	(-2.68)	(-4.63)	(-4.65)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.069	0.059	0.055	0.063	0.085	0.098	0.083
Obs.	253868	227214	202351	117170	561609	553651	443884

Table IA.12: Reaction of sales and margin forecasts to ESG incidents, balanced sample

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

Panel A: At least one incident

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
>=1 incidents in months [t-6,t]	-0.052**	-0.045**	-0.039*	-0.002	-0.023*	-0.037***	-0.052***	-0.033*	-0.026	0.006	0.018	-0.027**	-0.028**	-0.013
	(-2.25)	(-2.05)	(-1.82)	(-0.13)	(-1.91)	(-2.82)	(-3.25)	(-1.81)	(-1.37)	(0.33)	(1.12)	(-2.49)	(-2.21)	(-1.04)
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	0.110	0.112	0.112	0.105	0.100	0.115	0.091	0.056	0.047	0.044	0.050	0.055	0.049	0.044
Obs.	132628	120672	105915	61519	347954	337317	221502	132628	120672	105915	61519	347954	337317	221502

Panel B: Splitting by the number of incidents

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
1 incident in months [t-6,t]	-0.038	-0.033	-0.023	0.015	-0.017	-0.023*	-0.035**	-0.040**	-0.021	0.015	0.019	-0.030**	-0.026*	-0.000
	(-1.65)	(-1.44)	(-1.07)	(0.87)	(-1.42)	(-1.72)	(-2.15)	(-2.18)	(-1.12)	(0.75)	(1.13)	(-2.32)	(-1.94)	(-0.02)
>=2 incidents in months [t-6,t]	-0.084***	-0.073**	-0.075**	-0.040*	-0.036**	-0.068***	-0.088***	-0.019	-0.036	-0.014	0.017	-0.020	-0.032**	-0.041**
	(-2.63)	(-2.45)	(-2.56)	(-1.76)	(-2.15)	(-3.77)	(-3.96)	(-0.72)	(-1.47)	(-0.57)	(0.75)	(-1.51)	(-2.07)	(-2.39)
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	0.110	0.112	0.112	0.105	0.100	0.115	0.091	0.056	0.047	0.044	0.050	0.055	0.049	0.044
Obs.	132628	120672	105915	61519	347954	337317	221502	132628	120672	105915	61519	347954	337317	221502

Table IA.13: 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 is equal to one if at least one ESG incident happens in months $[t-6, t]$, and zero otherwise. The second independent variable is equal to one if at least one negative KD incident happens in months $[t-6, t]$, and 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 levels. 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
>=1 ESG Incidents in months [t-6,t]	-0.035***	-0.054***	-0.060***	-0.035***	-0.035***
	(-3.84)	(-4.79)	(-5.10)	(-3.85)	(-3.85)
>= 1 KD Negative Incidents in months [t-6,t]	-0.054***	-0.060***	-0.032***	-0.054***	-0.054***
	(-5.81)	(-5.51)	(-2.66)	(-5.96)	(-5.96)
>=1 ESG Incidents in months [t-6,t] × 2-year				-0.019**	
				(-2.58)	
>= 1 KD Negative Incidents in months [t-6,t] × 2-year				-0.006	
				(-0.86)	
>=1 ESG Incidents in months [t-6,t] × 3-year					-0.025**
					(-2.37)
>= 1 KD Negative Incidents in months [t-6,t] × 3-year					0.022**
					(2.07)
$\beta_{ESG\times h-year} - \beta_{KD\times h-year}$				-0.013	-0.047
F-stat				1.745	10.121
P value				0.189	0.002
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	0.084	0.097	0.083	0.091	0.085
Obs.	635164	622480	480707	1257644	1115871

Table IA.14: Reaction of earnings forecasts excluding employee-related incidents

This table reports the results of regressions of changes in EPS consensus forecasts, PTG, and returns 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 return in month t. In Panel A, the independent variable is a dummy variable equal to one if at least one employee-unrelated incident happens in months $[t-6, t]$ and zero otherwise. In Panel B, the independent variables are two dummy variables equal to one if one employee-unrelated incident happens in months $[t-6, t]$ and if at least two employee-unrelated incidents happen in months $[t-6, t]$, respectively. Employee-unrelated incidents are RepRisk incidents excluding "poor employment conditions", "supply chain issues", "freedom of association and collective bargaining" and "occupational health and safety issues". Standard errors are double clustered at the firm and month levels. 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 employee-unrelated ESG incidents in months [t-6,t]	-0.137**	-0.119*	-0.075	-0.053	-0.144***	-0.153***	-0.160***	-0.001	-0.165***	-0.171***
	(-2.07)	(-1.78)	(-1.16)	(-0.91)	(-3.43)	(-3.82)	(-4.14)	(-0.12)	(-5.86)	(-4.83)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Panel B: Splitting by the number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 employee-unrelated ESG incident in months [t-6,t]	-0.076	-0.058	-0.006	-0.031	-0.105**	-0.113***	-0.125***	0.010	-0.128***	-0.160***
	(-1.07)	(-0.82)	(-0.09)	(-0.53)	(-2.47)	(-2.70)	(-3.06)	(0.79)	(-4.50)	(-4.56)
>=2 employee-unrelated ESG incidents in months [t-6,t]	-0.275***	-0.257***	-0.232**	-0.102	-0.234***	-0.246***	-0.237***	-0.026	-0.250***	-0.196***
	(-3.06)	(-2.86)	(-2.58)	(-1.17)	(-3.95)	(-4.58)	(-4.57)	(-1.58)	(-6.46)	(-3.81)
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	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295232	272346	249829	150188	661466	649616	500617	226021	645591	638384

Table IA.15: 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 basis points). In Column (3), the dependent variable is the estimated change in firm value resulting from EPS changes only (in %) in month t, defined in Section 5.2. In Column (4), the dependent variable is the cumulative return (in %) over the month t. In Column (5), the dependent variable is the change in the PTGs (in %), defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. The independent variable is equal to 1 if at least one incident happens in months $[t-6, t]$ and 0 otherwise. The regression uses only the US sample. Standard errors are double clustered at the firm and month levels. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	$\Delta r_{i,t}(bps)$	$\frac{\Delta r_{i,t}}{r_{i,t-1}}(bps)$	$\frac{\widehat{\Delta PV_{i,t}}}{PV_{i,t-1}}$	$Ret.$	$\frac{\Delta PTG_{i,t}}{PTG_{i,t-1}}$
	(1)	(2)	(3)	(4)	(5)
>=1 incidents in months [t-6,t]	0.004	-0.456	-0.191**	-0.118*	-0.156***
	(0.03)	(-0.25)	(-2.41)	(-1.81)	(-3.13)
Month $\times$ Industry FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
adj R2	0.362	0.380	0.039	0.342	0.165
Obs.	160152	160152	160152	160152	160152