How do ESG incidents affect firm value?

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Abstract

We investigate how sell-side analysts adjust their earnings forecasts following ESG incidents. We find that following negative ESG news, analysts significantly downgrade their earnings forecasts at all horizons, including long-term. Forecast revisions account for all the negative impact of ESG incidents on firm values, implying no change in the discount rate. The negative revision of earnings forecasts reflects lower expectations on future sales (rather than higher future costs). In Europe, analysts who exhibit a stronger sensitivity to ESG news provide significantly more precise forecasts than their peers.

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1 Introduction

The use of environmental, social, and governance (ESG) information is a rising theme in asset management. Bryan et al. (2020) identifies 534 sustainable index mutual funds and exchange-traded funds globally, with collective assets under management of $250 billion. The money invested in them has more than doubled over the past three years. Launched in 2006, the UN supported Principles for Responsible Investment (PRI) initiative has gathered more than 3,000 signatories, managing over $103 trillion AUM. Signatories of the PRI commit to "incorporate ESG issues into investment analysis and decision-making processes" and Gibson et al. (2021b) find that more than half of global institutionally owned public equity is now held by PRI signatories.

While ESG is receiving increasing attention not only in practitioner circles, but also from academics, the issue of how much ESG information matters for firm value is still widely debated. In addition, it is poorly understood through which channels–if any–ESG news affects the value of firms.

A first channel through which ESG might affect firm value is related to the impact of divestitures on firms' cost of capital. If firms with poor ESG reputation are shunned by a large enough pool of investors their cost of capital should be higher and hence firm values should be lower. Such a *discount rate* channel is modeled by Heinkel et al. (2001) and more recently Pastor et al. (2019) and is empirically tested in Hong and Kacperczyk (2009) and Bolton and Kacperczyk (2019).

A second channel through which ESG could potentially affect stock-market values is if ESG metrics are predictors of future earnings of the firm. For instance, if a firm is subject to negative ESG news, such as the publication of high levels of pollution, shareholders might expect lower future earnings, due to binding regulatory constraints, potential liabilities, or negative reactions from customers. Such real implications of ESG information for firm fundamentals might be either short-term (e.g. through a fine or settlement of a lawsuit), but could also impact long-term earnings, for instance if stakeholders such as customers or employees structurally turn their back on the firms with poor ESG profiles. If some investors are unaware of the importance of ESG information for future earnings, such information might predict both contemporaneous and future returns. This *cash flow* channel is modeled in Pedersen et al. (2019) and evidence of under-reaction is presented in Edmans (2011).

The main goal of our study is to empirically disentangle and measure the relevance of the *discount rate* and *cash flow* channels in shaping the relation between firm value and a firms ESG profiles. To do so, we combine a global sample of analyst forecasts of earnings, sales, and margins at various horizons with ESG news data. Analyst forecast data serve as a proxy for expectations about future firm fundamentals. The ESG news data capture salient negative point-in-time shocks to analysts beliefs about the ESG characteristics of firms. Our approach is to explore whether and how analysts change their earnings forecasts as a result of news about negative ESG incidents. Using ESG news data rather than ESG ratings (or scores) allows us to avoid the well-documented inconsistency of ESG ratings. For instance, Berg et al. (2019) or Gibson et al. (2021a) document disagreement of ESG scores issued by different data providers. In addition, Berg et al. (2020) document back-filling issues in Refinitiv ESG data, a widely used ESG dataset. Besides the mentioned methodological issues, another concern with using ESG scores is that these scores are typically slow-moving and it is difficult to isolate why and when ESG scores change. Focusing on news-related ESG data allows us to identify precise shocks to the ESG-information set of financial analysts.

Our analysis delivers several novel stylized facts. It proceeds as follows. Section 2 details the different data sets and variables used in our study. Section 3 describes our core results on whether and how analysts update their forecasts following ESG news. We provide evidence that negative ESG news shift earnings forecasts at short *and* long horizons. The reaction is stronger when firms are subject to multiple news incidents and when the news are related to social issues. We also find that implications of negative ESG news for future earnings are not redundant with other proxies of firm quality (e.g., profitability) available at the time the news occur, suggesting that ESG news are not spanned by existing accounting information. Section 4 decomposes valuation effects of ESG news into *cash flow* and *discount rate* effects. Using a simple Dividend Discount approach, we show that changes in earnings forecasts account for all the negative reaction in firm valuations following ESG incidents. The implied change in discount rate is not statistically significant from zero. Section 5 further decomposes earnings revisions into a component coming from sales revisions and a component coming from costs revisions. Our analysis suggests that the changes in analysts' earnings expectations are primarily driven by an anticipation of lower sales rather than higher future costs. Section 6 studies the heterogeneity of our result on forecasts revisions across geographic regions, industries, and firm sizes. We find that our forecasts revision effect is stronger for smaller firms and in B-to-C sectors (where advertising expenses are higher). In the section 7,we asks whether analysts who are more sensitive to ESG news issue forecasts that are more precise or less precise than peers. We find that overall, ESG-sensitive analysts have more precise forecasts, but this is statistically significant only in Europe. Section 8 concludes.

Literature Review. According to a widely cited meta-study (see Friede et al. (2015)) the majority of prior research documents a nonnegative association between a firms ESG policies and measures of financial performance. However, the exact mechanisms through which ESG translates into financial performance or firm value remain ambiguous and it is often hard to establish the direction of causation (Hong et al. (2012)). While prior research documents mostly correlational evidence, some papers have attempted to identify specific mechanisms through which ESG might affect cash flows or discount rates. For instance, Servaes and Tamayo (2013) stress that a firms ESG policies can affect consumer behavior, thereby enhancing cash flows and firm value. In a similar spirit, Krueger et al. (2021) focus on another key stakeholder (i.e., workers) and provide evidence that firms with better ESG policies pay lower wages, highlighting that ESG policies might generate higher value for shareholders through a reduction in labor costs. Other papers focus on the effect of ESG on the cost of capital and provide evidence that better ESG policies are associated with lower cost of capital (e.g., Chava (2014), Dunn et al. (2018), Albuquerque et al. (2019)). Overall, however, the extent to which asset prices incorporate, or do not incorporate, sustainability, and whether this is through a cash flow and/or cost of capital channel is still relatively poorly understood.

Other papers in the finance literature have examined a variety of ESG-related topics. For instance, Lins et al. (2017) study whether stock markets valued better ESG policies during the Great Financial Crisis. Using the introduction of the Morningstar ESG rating, Hartzmark and Sussman (2018) examine if investors care about a mutual funds ESG characteristics. Liang and Renneboog (2017) explore determinants of corporate social responsibility policies and highlight the important role of the legal origins of the country in which a firm is headquartered. Ferrell et al. (2016) empirically study how sustainability relates to agency issues and find a positive correlation between ESG scores and firm value. Other papers have used experimental methods to shed light on why investor hold socially responsible mutual funds (see Riedl and Smeets (2017)), whether individuals are willing to use their pension savings to promote sustainability (Bauer et al. (2019)), or whether shareholders value a firm's ethical actions (see Bonnefon et al. (2019)). Given the dearth of finance theory on how to think about ESG investing, a host of theory papers concerned with sustainability and ESG have emerged recently. For example, Pastor et al. (2019) develop a theoretical model to study the financial and real effects of sustainable investing. Pedersen et al. (2019) develop a theory of the potential costs and benefits of ESG-based investing and derive an ESG-efficient frontier. Oehmke and Opp (2019) develop a theory of socially responsible investment and Landier and Lovo (2020) study whether and how sustainable finance can have a real impact in reducing negative externalities. Related to our work are two concurrent working papers, which also use Reprisk data. For example, Gloßner (2018) finds that negative ESG informational shocks predict negative future stock returns, suggesting under-reaction by the stock markets regarding such information. Gantchev et al. (2020) provide empirical evidence on exit by institutional investors following negative E&S shocks. They also document that firms with more E&S motivated investors and customers experience temporary declines in valuations followed by improvements in their E&S policies.

2 Data

2.1 Reprisk and other ESG scores

Our main ESG data come from RepRisk. RepRisk produces daily indicators about negative ESG-related incidents at the firm-level. It does so through the daily analysis of a large set of documents from public sources in 20 languages. The data goes back to January 2007, with daily granularity. RepRisk classifies all the ESG incidents into 28 distinct issues. Environmental issues include news about climate change, pollution, waste issues, etc. Social issues include child labor, human rights abuses, etc. Governance issues include executive compensation issues, corruption, etc.[1] One incident can be associated with multiple issues, and therefore can belong to two or more E/S/G categories. Table IA2 shows the distribution of incidents types. Around half of the incidents are associated with two or more E/S/G categories. Figure 1 shows the average number of monthly incidents by year. The number of ESG incidents recorded by RepRisk increases with time. Social issues are the most populated in the sample. At the beginning of the sample there are more

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

environmental than governance incidents, while at the end of the sample there are more governance incidents. In addition, RepRisk categorizes the ESG incidents based on their novelty, reach, and severity. Novelty, reach, and severity of incidents are on a scale from 1 to 3, where 3 represent the most novel, most influential or most severe incidents.

Figure 1 about here.

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

2.2 IBES

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

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

To match monthly IBES consensus forecasts with RepRisk data, we aggregate all the RepRisk ESG incidents between two summary statistics dates to the monthly level. Specifically, for two consecutive consensus forecast summary statistics dates d_{t-1} and d_t, we consider ESG incidents published at dates within $[d_{t-1}, d_t)$ as 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 in month t ($num\_incidents$). Figure 2 illustrates the timing of the merge. In this example, three incidents are reported during $[d_{t-1}, d_t)$, so in month t, $incidents_t = 1$ and $num\_incidents_t = 3$. No ESG incidents are

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

reported during $[d_t, d_{t+1})$, so $incidents_{t+1} = 0$ and $num\_incidents_{t+1} = 0$.

Figure 2 about here.

2.3 Stock returns and fundamentals

We collect US daily stock returns from CRSP, and daily stock returns of international firms and firm fundamentals from Compustat. We merge CRSP/Compustat with IBES by the last trading day before the IBES consensus forecast date. For the US companies, we match Compustat-CRSP with IBES using CUSIP. For international companies, we match Compustat with IBES using SEDOL. We merge Compustat with IBES using the last observable financial statement on the consensus forecast date. We consider a financial statement as observable only after the earnings announcement (or publication) date rather than fiscal year end date to avoid the look-ahead bias. To make firms in the international sample comparable, we translate all other currencies to US dollars using daily exchange rates. In some of the tests we use advertisement spending of firms, which is only available for the U.S. sample but still has a large fraction of missing values. We first construct the firm-level advertisement intensity, which is defined as scaled advertisement spending by revenue. We then take the median advertisement intensity of each industry (GICS2) as industry-level advertisement intensity, and assign the measure to all the firms in the industry.

We merge the CRSP-Compustat-IBES sample with RepRisk using ISIN. We require the firm to exist in all the data sources to be included in the final sample.

2.4 Key variables construction

We focus on changes in the forecasts. For EPS forecast F_tEPS_{t+h} made at month t for horizon h, we define the change in the EPS forecast as $\Delta F_tEPS_{t+h} = \frac{F_tEPS_{t+h} - F_{t-1}EPS_{t+h}}{abs(F_{t-1}EPS_{t+h})}$. We scale the forecast change by the absolute value of the initial forecast to deal with negative forecasts.[3] Similarly, the change in PTG is defined as $\Delta PTG_t = \frac{PTG_t - PTG_{t-1}}{PTG_{t-1}}$. We drop negative sales forecasts and negative gross margin forecasts (less than 0.5% of our sample), and define the change in sales forecasts as $\Delta F_tSales_{t+h} = \frac{F_tSales_{t+h} - F_{t-1}Sales_{t+h}}{F_{t-1}Sales_{t+h}}$, and the change in gross margin forecasts as $\Delta F_tGrossMargin_{t+h} = \frac{F_tGrossMargin_{t+h} - F_{t-1}GrossMargin_{t+h}}{F_{t-1}GrossMargin_{t+h}}$. Since long-term growth (LTG) forecasts are already in percentage points, we define the change in LTG forecast as $\Delta LTG = LTG_t - LTG_{t-1}$.

In our regressions, we control for the observed change in the key fundamentals of the firms. We first forward fill the annual accounting variables to the monthly level, time stamped based on the financial statement publication date. Next, we construct the changes in 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 non-zero 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.

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

Our final sample includes 8054 firms from 45 countries (regions).[4] There are 2,635,412 firm-month-horizon level EPS forecasts observations, 2,538,492 firm-month-horizon level sales forecasts observations, 1,271,860 firm-month-horizon level gross margin forecasts observations, 604,370 firm-month level PTG forecasts, and 226,939 firm-month level LTG forecasts. In the full sample, 7.43% of observations have exactly one ESG incident and 4.73% of observations have at least two ESG incidents. Table 1 reports the summary statistics of the main variables we use in the analysis.

Table 1 about here.

3 Baseline: Reaction to ESG incidents

3.1 Event Study

In this section, we start our analysis by examining how ESG-related news induce changes in analyst forecasts and analyze the determinants of these changes. We examine whether analysts react to incidents by changing their earnings forecasts and whether they change their forecasts differentially for different horizons. To do so, we use the daily analyst forecasts to conduct an event study. A firm with an incident on date d_t is considered a "treated" firm. Each treated firm is matched to a control

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

firm, i.e., a firm in the same industry and country as the treated firm but with no ESG incident in $[d_t - 30, d_t]$. Among all potential control firms, we choose the one that is the closest to the treated firm in terms of market capitalization one day before the ESG news day d_t. As we know in one month firms can have multiple ESG incidents and hence to avoid overestimating the impact of each incident, we focus on observations with no other incident in the previous 90 days. To further control for the pre-trend and valuation differences of the treated and control firms, for each day s after the ESG incident, we run the following regression:

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

where the dependent variable is the difference between the change in the scaled forecast of treated and control firms at the same horizon at date $d_t + s$ (see section 2.4 for details on the definition of forecast changes).[5] $\Delta(F_{d_t-1} EPS_{i,d_t+h} - F_{d_t-180} EPS_{i,d_t+h})$ is the difference in EPS change between treated and control firms 180 days before the ESG incident. This is to control for the pre-trend of EPS forecasts change. $\Delta(B/M)_{i,d_t-1}$ is the difference in book to market ratio one day before the occurrence of the ESG incident, which is used to control for the market valuation of the firms before the ESG incident occurs. The coefficient estimate of interest is α_s, which measures the difference in forecast changes between treated and control firms s days after the incident. We estimate similar regressions for PTG, Raw Return, and FF3-alpha.

[5] We scale the EPS forecasts using the EPS forecasts one day before the ESG incidents, i.e, $d_t - 1$.

The regression that uses FF3-alpha as the dependent variable is estimated only for the US sample and risk adjustment is carried out using the Fama and French (1993) three factor model.

Figure 3 about here.

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

3.2 Panel Regression Analysis

We now explore the patterns documented in the previous section in a regression setting. The regression analysis allows to estimate the term structure of how analysts change their forecasts following incidents. The objective is to better understand whether analysts believe that ESG incidents have only a short-term effect on profits, or instead reflect issues that will materialize mostly at longer horizons. For this analysis, we consider forecasts at different horizons separately. Specifically, we use forecasts at the one-quarter to three year horizon and estimate for each horizon h the following regression:

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

The dependent variable is the change in consensus EPS forecasts between two consecutive months $t-1$ and t, scaled by the absolute value of the consensus EPS forecast in month $t-1$. We also consider analysts price targets and calculate the change in the consensus price target between months $t-1$ and t scaled by the price target in month $t-1$. The main independent variable in these tests is an indicator variable equal to one if Reprisk reports at least one ESG incident between month $t-6$ and t. We accumulate the ESG incidents in months $[t-6, t]$ to take into account the under-reaction in analyts forecast revisions[6]. We include firm fixed effects in these regressions as the number of ESG events varies significantly across firms and

[6]Our results are robust to accumulating ESG incidents in months $[t-3, t]$, $[t-9, t]$ or $[t-12, t]$. The result appears in Table IA4

is explained by time-invariant firm characteristics[7]. To account for the strong industry effect in ESG events and its time-varying and location-varying nature, we also include month $\times$ industry $\times$ country fixed effects in these regressions. We cluster standard errors at the industry-month level to account for the possible time-varying dependence across industries[8].

Table 2 about here.

Panel A of Table 2 shows that the effect of ESG incidents on earnings forecasts is negative at all horizons, statistically significant at most horizons, and approximately constant across horizons. For example, the monthly change in earnings forecasts at the one-quarter horizon (-0.158 percentage points) is roughly equal to that at the two- or three-year horizons (-0.143 and -0.150 percentage points, respectively). We conclude that following ESG incidents, there is an almost-parallel shift in analysts EPS forecasts. This is confirmed in Column 8, in which the effect of ESG incidents on the forecasted long-term growth of EPS is economically and statistically insignificant. The last two columns of the table report the relative change in price targets, and the stock return following ESG incidents. In line with the finding of Figure 3, the two are significantly negative and of similar magnitudes.

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

[8] The results discussed below are robust to clustering standard errors by firms. The result appears in Table IA5

In Panel B of Table 2, we refine the analysis by considering how the number of incidents in a given six-month period affects EPS forecasts, price targets and returns. Intuition suggests that analysts reactions should increase with the number of incidents. In line with this intuition, the reactions are significantly more pronounced for firms that have at least two incidents in the last six months compared to firms that report only one incident, both economically and statistically speaking. For example, decreases in EPS forecasts vary from around 0 to -0.113 percentage points across all forecast horizons for firms with one incident in the past six months, while they vary between -0.125 and -0.302 percentage points for firms with at least two incidents in the same period. Again, firms with the strongest analyst reactions, i.e., those with at least two negative ESG events reported by Reprisk in the last six months see a change in the EPS forecasts of analysts that is roughly constant across all horizons.

To explore the term structure of analysts reactions to ESG events in greater detail, we now contrast the reaction to ESG events with analysts reactions to other informational shocks. Our goal is to investigate whether ESG events have a stronger impact over the long-run than the typical informational shock affecting short-term earnings. Hence, instead of focusing on specific news and exploring analysts reactions to these news, we examine the sensitivity of forecast changes at different horizons to forecast changes at the one-year horizon. By doing so, we implicitly assume that forecast changes at all horizons are driven by the same unobserved news, and we measure the relative effect of the average news on the term structure of forecast changes. For each horizon h, we run the following regression:

$$\frac{\Delta F_t EPS_{i,t+h}}{F_{t-1}EPS_{i,t+h}} = \alpha + \beta \frac{\Delta F_t EPS_{i,t+1}}{F_{t-1}EPS_{i,t+1}} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t} \qquad (3)$$

Table 3 reports the estimation results of the equation above. The last two columns report the change in the average price target and the contemporaneous stock return to a one-percent change in one-year EPS forecasts. Overall, the magnitude of the coefficients is similar to that of coefficients on the same variables in previous tables (about 0.15% on average), implying that a one-percent change in EPS forecast caused by an average event has about the same impact on firm value as an ESG event in our sample. However, the effect of average events on forecasts seems more short-lived than that of ESG events. While the effect of ESG events on forecasts is relatively stable over time, as seen in Table 2, an event that causes a one-percent decline in one-year EPS forecasts, causes an average decline of 0.412% (respectively, 0.255%) on two-year (respectively, three-year) forecasts.

Table 3 about here.

Appendix Table IA9 reports analyst reactions by type of incidents. The impact of E incidents on forecast changes appears to be less significant than that of incidents concerning S and G matters. S and G incidents have about the same effect. The insignificance of E incidents is likely due to E incidents reported by Reprisk not being as serious as incidents in the two other categories. In Appendix Table IA10, we split the treatment by one incident and two or more incidents. In months with more than one E incident, there is a significantly negative effect on analyst forecast, which implies that analysts react more when there is a series of negative environmental incidents. Appendix Table IA11 reports the regression where we only consider the incidents for which Reprisk's reach, novelty, and severity measure is equal to or larger than 2. The effect of novel incidents is not different from that of other incidents. However, high reach and high severity incidents have stronger effects than other incidents. In the rest of the analysis we do not differentiate across the ESG incidents.

4 Impact on firm values: cash flows vs. discount rates

There are two reasons why stock values might decrease after the occurrence of negative ESG events. The first one is downward revisions in expected future earnings. The second one is that the cost of capital might have increased, reflecting a smaller set of available investors (some investors exclude firms with low ESG performance) or a higher level of perceived systematic risk. We propose in this section to empirically decompose the valuation effects of ESG shocks by disentangling effects that come from forecasted profits and effects resulting from changes in discount rate.

4.1 A first intuitive pass using Gordon's formula

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

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

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

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

But in our data, Table 2 suggests that the impact of ESG incidents leaves expected growth unchanged ($\Delta g \simeq 0$), while the similarity of the coefficient in column (10) with the coefficients of columns 6-7 translates to: $\frac{\Delta PV_{it}}{PV_{it}} \simeq \frac{\Delta F_t EPS_{i,t+1}}{F_t EPS_{i,t+1}}$.
Hence, going back to Equation 4, the coefficients observed in Table 3 suggest that

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

which means that there is no change in the discount rate and that changes in expected future earnings account for all the change in firms' equity values induced by a typical ESG incident.

4.2 A discounted dividends approach

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

$$\frac{PV_{it}(r_{it})}{b_i} = \frac{F_tEPS_{i,t+1}}{(1+r_{it})^{\theta_{it}}} + \frac{F_tEPS_{i,t+2}}{(1+r_{it})^{\theta_{it}+1}} + \frac{F_tEPS_{i,t+3}}{(1+r_{it})^{\theta_{it}+2}} + \frac{1}{(1+r_{it})^{\theta_{it}+2}}\frac{(1+g_t)F_tEPS_{i,t+3}}{r_{it}-g_t}$$

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

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

where P_{it} is the stock price of firm i at time t. We only keep values of this discount rate r_{it} between 0 and 30%. Our null hypothesis is that ESG incidents do not affect discount rates used to compute firm values. To explore this hypothesis, we run regressions similar to Equation 2, replacing EPS forecasts with Δr_{it}, expressed in absolute or relative terms.

Table 4 about here.

Columns (1) and (2) of Table 4 report the results. In the two columns, the coefficient on ESG incidents is marginal and statistically insignificant. In other words, ESG incidents have no impact on the estimated implied rate of return. This suggests that ESG incidents affect the market value of firms only through the cash flow channel. To confirm this, we use a slightly different approach. Each month t and for each firm i, we compute the new firm value using the formula above, with updated analyst forecasts and the same discount rate, growth rate and payout ratio as in month $t-1$. We then calculate the percentage change in value between months $t-1$ and t, $\widehat{\Delta PV_{i,t}}/PV_{i,t-1}$, which is the predicted stock return if ESG shocks affect only expected profitability but not the discount rate. We check how ESG incidents affect this predicted return using the same regression setting as above. In Column (3) of Table 4, the coefficient on the number of incidents is significantly negative and of a similar magnitude compared to that of returns or price target changes observed in Table 2. In other words, using the simple valuation formula above, changes in earnings forecasts alone predict the changes in firm values observed (using returns) or predicted (using analysts price targets). Columns (4) and (5) of Table 4 confirm that in the US sample, the effect of ESG incidents on observed (column (4)) and predicted (column (5)) returns is comparable to the effect of earnings changes alone on returns using our estimated firm value formula. Taken together, the evidence from Table 4 suggests that ESG incidents affect firm value through a profitability channel rather than through a discount rate channel.

5 Economic Mechanism: Sales vs. Costs

Why do analysts anticipate such long-term earnings decreases following the occurrence of ESG incidents? There are two main economic mechanisms at play. First, it could be that analysts expect customers to avoid buying from firms that fail to comply with ESG standards. Second, future earnings could also decrease (even if sales are stable) if ESG incidents lead to increased costs, for example due to costs of adjusting to existing or future ESG regulation, or simply because ESG incidents lead to monetary penalties for the firms involved.

To understand through which of these two channels (sales vs. costs) analysts anticipate earnings to be affected by negative ESG incidents, we run two sets of regressions similar to Equation 2, replacing changes in earnings forecasts by changes in sales forecasts ($\frac{\Delta F_t Sales_{i,t+h}}{F_{t-1} Sales_{i,t+h}}$) and changes in gross margin forecasts ($\frac{\Delta F_t GrossMargin_{i,t+h}}{F_{t-1} GrossMargin_{i,t+h}}$) also issued by security analysts.

Table 5 reports the results of these regressions, which suggest that the anticipated decrease in earnings documented earlier is expected to happen through a reduction in sales. The coefficients on the ESG incident dummy variable are consistently negative in column 1-7 Panel A and statistically significant at most horizons. Column 1-7 of Panel B suggest that this effect is more pronounced for firms with multiple incidents, as is the case for earnings forecasts. The evidence from margin regressions (in column 8 to 14) is less clear. Following ESG incidents, analysts tend to revise downwards their margin forecasts only at very short (i.e., one quarter) and 1-year horizons, but not at other horizons. In addition, the coefficient estimates on the incident dummies are only weakly significant. Overall, these results suggest that analysts expect ESG incidents to affect future earnings mostly through a reduction in sales.

Table 5 about here.

6 Heterogeneity

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

6.1 Variation across Geographic Regions

First, we analyze heterogeneity across countries, splitting the sample by geographic regions. It is possible that downward adjustment of sales and earnings are due to consumers' preferences in some of the regions but not others. To test this hypothesis, we use firms located in North America (U.S. and Canada) as the baseline, and further interact the ESG incidents variables with dummies indicating $EU15$, $Asia$ and $Others$, where $EU15$ indicates the 15 most developed countries in Europe as defined by the United Nations[9] and $Others$ mostly includes firms in South America, Australia, and Africa. We focus on the annual forecasts as U.S. firms dominate in quarterly forecasts.

Table 6 about here.

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

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

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

6.2 Variation across industries

Next, we ask whether the link between ESG-related news and analyst forecasts is more prevalent in some industries. Industries vary significantly in their exposure to ESG events. For example, firms in the energy industry are more likely to have ESG incidents in an average month than firms in the consumer services industry. The average number of incidents by industry is shown in Figure 4. Also, our previous results show that ESG performance influences future earnings mostly through customer demand. Customers at different levels of the supply chain may not only have different access to information regarding the ESG practices of the firms from which they buy but also different sensitivities to the ESG practices of firms. Our hypothesis is that end customers are both less informed about and more sensitive to ESG practices of the firms they buy from, so that the effect of salient news like those reported by

Reprisk should be more pronounced in B to C industries than in B to B industries. To examine this possibility, we calculate first the analysts sensitivity to ESG news at the industry level using the same setting as in Table 2 above. We consider the average sensitivity of one-, two-, and three-year earnings forecasts to Reprisk news across all firms in each industry (defined at GICS2) as our industry-measure of ESG sensitivity.

Figure 4 about here.

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

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 4 plots the advertisement intensity of industries (measured as $\frac{Advertisement\ Expense}{Revenue}$) against the industry-level sensitivity of analyst forecasts to news, i.e., the coefficients obtained in Table 2 averaged at the industry level. Panel A of Figure 7 considers the sensitivity of earnings forecasts to ESG-related news, while Panel B considers the sensitivity of their price targets. Both panels show a downward-sloping relation, meaning that industries with larger advertisement expenses also tend to have analyst forecasts that are more sensitive to ESG news (i.e., that have more negative coefficients in the setting of Table 2). In Table 7, we split 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 advertisement spending. We then repeat the baseline analysis of Equation 2, adding to the regression the interaction between a dummy measuring high advertisement intensity and the indicator variable equal to one for firms with ESG events in the past six months. The effect of ESG incidents on EPS forecast revisions is stronger (more negative) for firms in B to C industries, in particular at the one- and two-year horizons (Panel A). Panel B of Table 7 suggests that sales forecast revisions after ESG incidents are also stronger for firms in B to C industries, at almost all horizons.

Table 7 about here.

6.3 Large vs. small firms

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

Table 8 about here.

7 Are ESG-sensitive analysts better or worse forecasters?

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

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

where $precision_{i,j}$ is the forecast precision of analyst j on firm i, defined as the rank of forecast error of EPS forecasts (we drop EPS where less than 3 analysts made forecasts), averaged to analyst-firm level. Following Bouchaud et al. (2019), we only keep forecasts that were issued 45 days after an announcement of total fiscal-year earnings. If an analyst issues multiple forecasts for the same firm and the same fiscal year during this 45-day period, we retain only the first forecast. $ESG\ sensitivity_j$ is the ESG sensitivity of analyst j, defined as the coefficient β^j of the following regression $\frac{\Delta F_t EPS^j}{abs(F_{t-1} EPS^j)} = \alpha + \beta^j \mathbb{1}\{ESG\ incidents\ in\ months\ [t-6, t]\}$, which we estimate for each analyst. We only consider 1-3 year ahead EPS forecasts when estimating the sensitivity. The control variables $X_{i,j}$ include $log(age)_j$ the natural logarithm of years since the first forecast of analyst i, $log(experience)_{i,j}$ the natural logarithm of years since analyst j following firm i, *specialty* the proportion of forecasts made for firm i out of total forecasts, $log(frequency)_j$ the natural logarithm of number of forecasts made per year, $log(coverage)_j$ the natural logarithm of firms followed by analyst j. σ_j is firm fixed effect, which absorbs the firm-level characteristics that are related to forecast precision.

Table 9 presents the results. The first column presents the regression with only firm fixed effects. In Column 2, we also control for characteristics of the analysts. In these two columns, the link between the precision of analysts and their sensitivity to ESG-related news is insignificant. The next columns, however, show a striking difference between the U.S. and developed Europe. While the ESG-sensitive analysts are not more precise in forecasting earnings for U.S. firms, they are in the developed Europe. This suggests that in the U.S., analysts sensitivity is a function of their personal taste or that of their brokers or clients, while in Europe, precision and sensitivity to ESG news are related, perhaps because ESG news have a greater impact on the operating performance of European firms.

Table 9 about here.

8 Conclusion

This paper examines how negative ESG news impact revisions of earnings forecasts by analysts. We document significant downward revisions of earnings forecasts at both short horizons (one quarter) and long horizons (three years). These downward revisions are due to negative revisions of future sales, suggesting that analysts expect consumers to react negatively to a deteriorating ESG performance. Interestingly, all of the negative impact on stock prices of these ESG news can be explained by changes in earnings forecasts. We show, in a simple discounting exercise that the discount rate implied by valuations does not change before and after negative ESG news. Moreover, analysts who are relatively sensitive to ESG news are also more accurate in their forecasts, suggesting that the integration of ESG concerns is actually rational rather than being a “fad”.

Our results show that avoiding negative ESG incidents is an important risk-management strategy for companies, as such incidents have a substantial impact on firms’ long-term earnings.

Appendix A: RepRisk vs. other ESG data

In this appendix, we validate that the ESG incidents we use for our analysis are indeed about ESG issues, not just general negative news about the firms. In addition, we want to confirm that ESG news reported by RepRisk are related to the more classic ESG scores and ratings provided by other ESG data providers. These ratings are not directly usable for our purpose because they are updated at low frequency and because the reasons for their change are not always clear. Furthermore, ESG scores produced by rating agencies aggregate several criteria, including ESG-related news and other quantitative and qualitative information provided by the firms themselves or by other sources. However, the way this information is processed and re-combined by rating agencies into ESG scores is not always entirely transparent. Moreover, rating agencies frequently change their rating methodologies (Berg et al., 2020), e.g., following acquisitions of other rating agencies , leading to time inconsistencies in their scores. As a result, the literature has found that scores provided by different rating agencies are sometimes difficult to reconcile (Berg et al., 2019). The advantage of using “ESG news” provided by RepRisk is to identify cleanly defined ESG-related events that are likely to affect a firm's ESG outlook. These news cover the E, S and G categories. They reflect salient events in each of these three categories. As such, they are well suited for our analysis. In this section, we want to confirm that ESG news reported by RepRisk are related to the more classic ESG ratings provided by Rating agencies.

To verify that, despite the reservations discussed above about ESG scores, there is indeed a link between RepRisk news and changes in ESG ratings, we compare Reprisk news with the scores provided by three of the most influential ESG rating agencies, namely, Asset 4 (now Refinitiv), MSCI, and Sustainalytics (now Morningstar). We regress ESG scores defined at the monthly level and their logarithms on the logarithm of the number of incidents reported by Reprisk in the preceding month:

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

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

The results reported in Table A1 show a clear connection between ESG scores and ESG-related news, with negative coefficients at all horizons and for the three scores considered. In all but two cases, the coefficients are also statistically significant at conventional levels. Comparing the results across score providers, we see that the results seem stronger, both economically and statistically, for Asset 4 and MSCI than they are for Sustainalytics, which might mean that ESG news-related data plays a lesser role in the construction of Sustainalytics scores. Overall, this evidence is consistent with the view that the ESG incidents we consider in our study are part of the information set used by providers of ESG scores.

Table A1: ESG incidents predict ESG scores

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

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

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Figures

Figure 1: Number of RepRisk ESG incidents by time

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

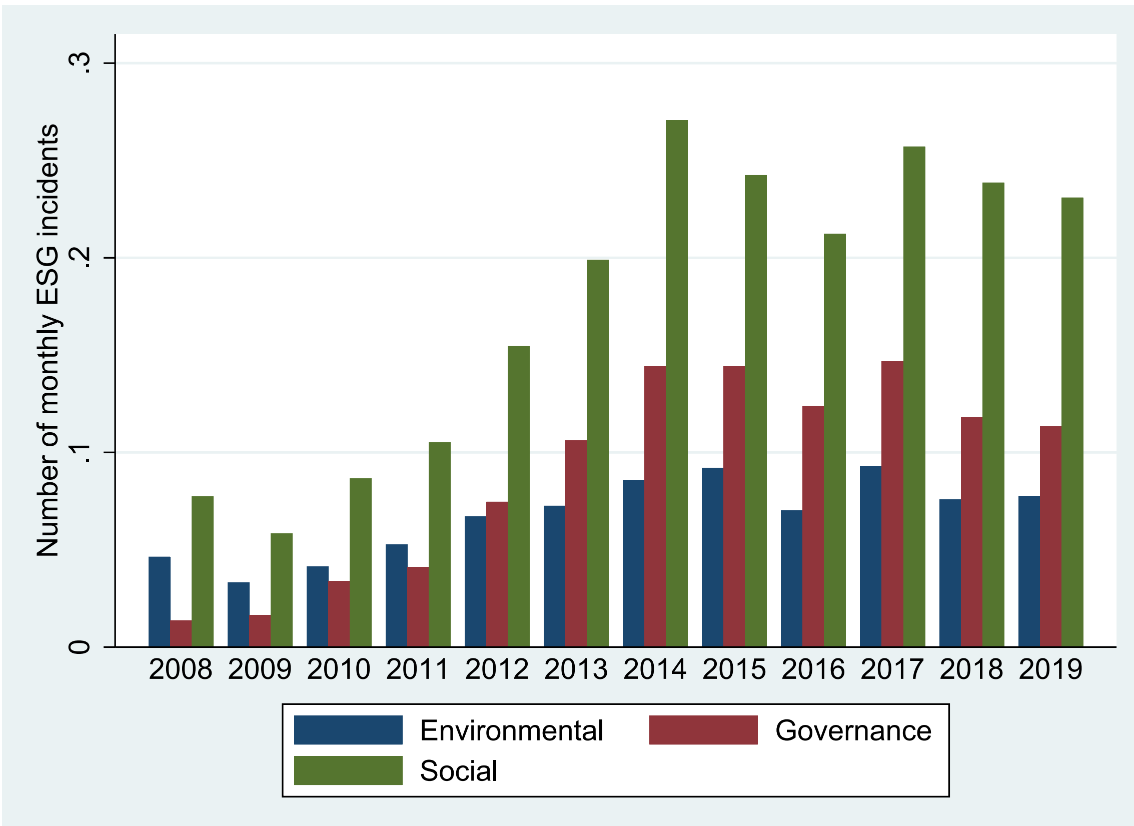


Figure 2: Timing of ESG incidents and analyst forecasts

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

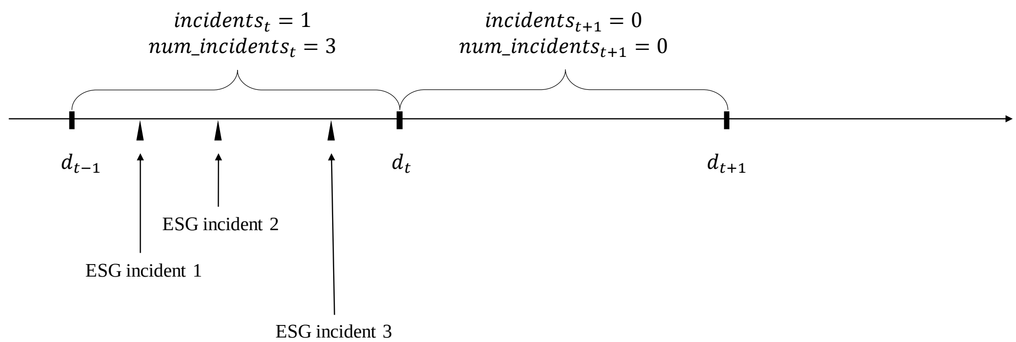
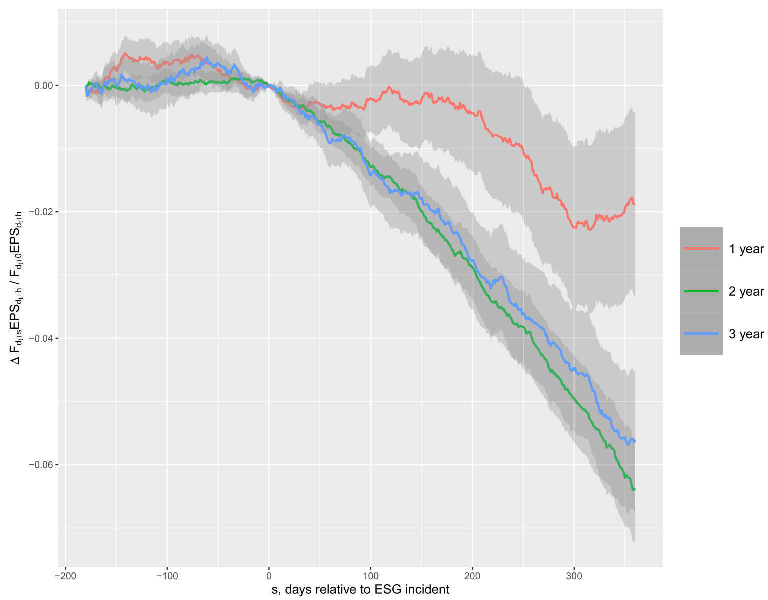


Figure 3: Daily EPS/PTG forecast change after incidents

This figure reports the result of a event study on ESG incident shocks. The horizontal axis is calendar days relative to ESG incidents. The vertical axis is the evolution of the difference in EPS and PTG forecast of (treated) firms that have ESG incidents on day 0, and the control firms. Specifically, for each ESG incident of each treated firm, the control firm is chosen as the firm that doesn't have ESG incidents within 30 days before day 0, and is in the same industry-country and has closest size to the treated firm. The y-axis is defined as the difference in EPS and PTG forecast after controlling for firm's value factor and trends before the ESG incidents. Specifically, for each day s, the difference is defined as the intercept α_s from $\Delta Y_{i,d_t+s} = \alpha_s + \beta_s \Delta(Y_{i,d_t-1} - Y_{i,d_t-180}) + \gamma_s \Delta B/M_{i,d_t-1} + \epsilon_{i,d_t}$, where Y are EPS/PTG forecasts, or return. We restrict the ESG incidents to the incidents where there are no other incidents for the treated firm within 90 days before day 0. Figure (a) shows the change for 1-year, 2-year, 3-year ahead EPS forecast. Figure (b) shows the change for price targets forecast, raw return, and excess return from FF 3-factor model (excess return is only for US sample).

(a) EPS forecast



(b) Price target and return

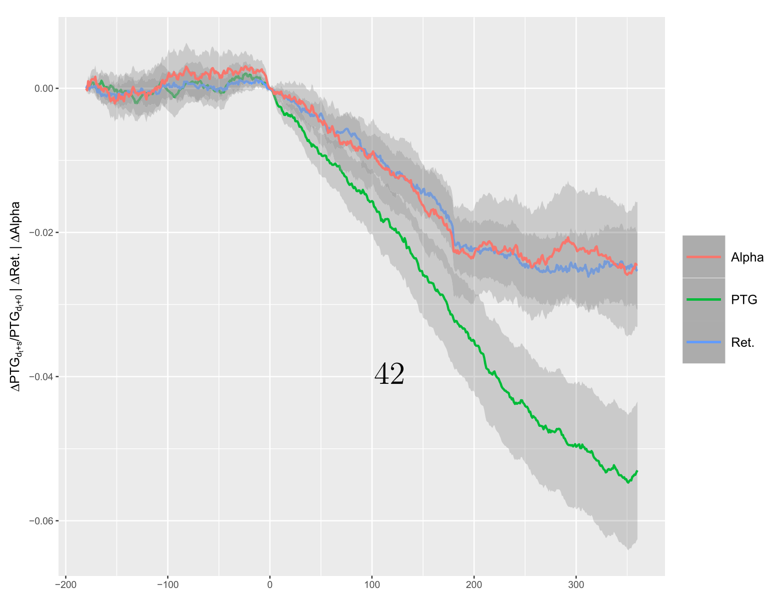


Figure 4: Number of incidents by industry

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

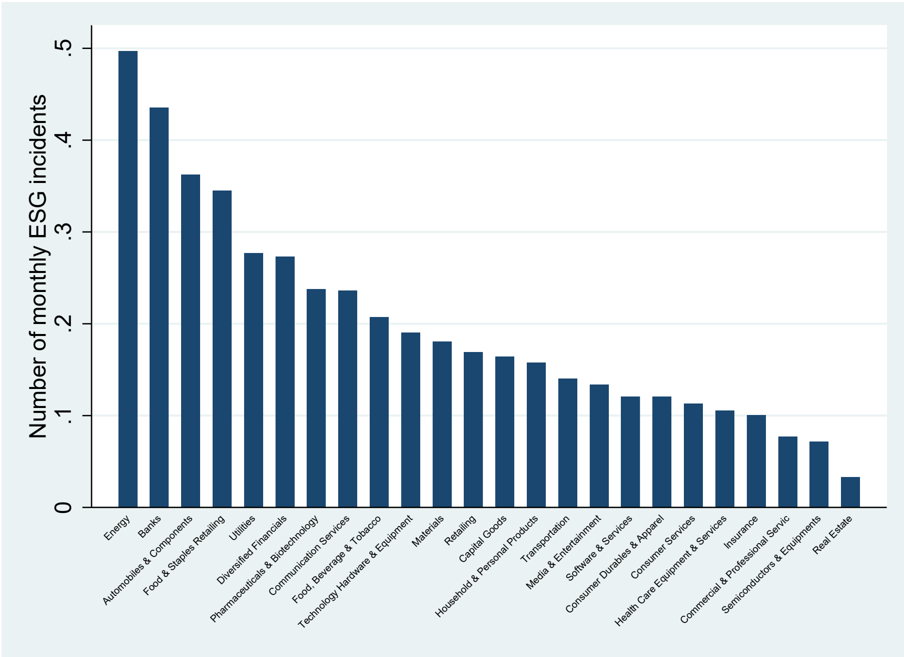


Figure 5: EPS sensitivity by industry

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

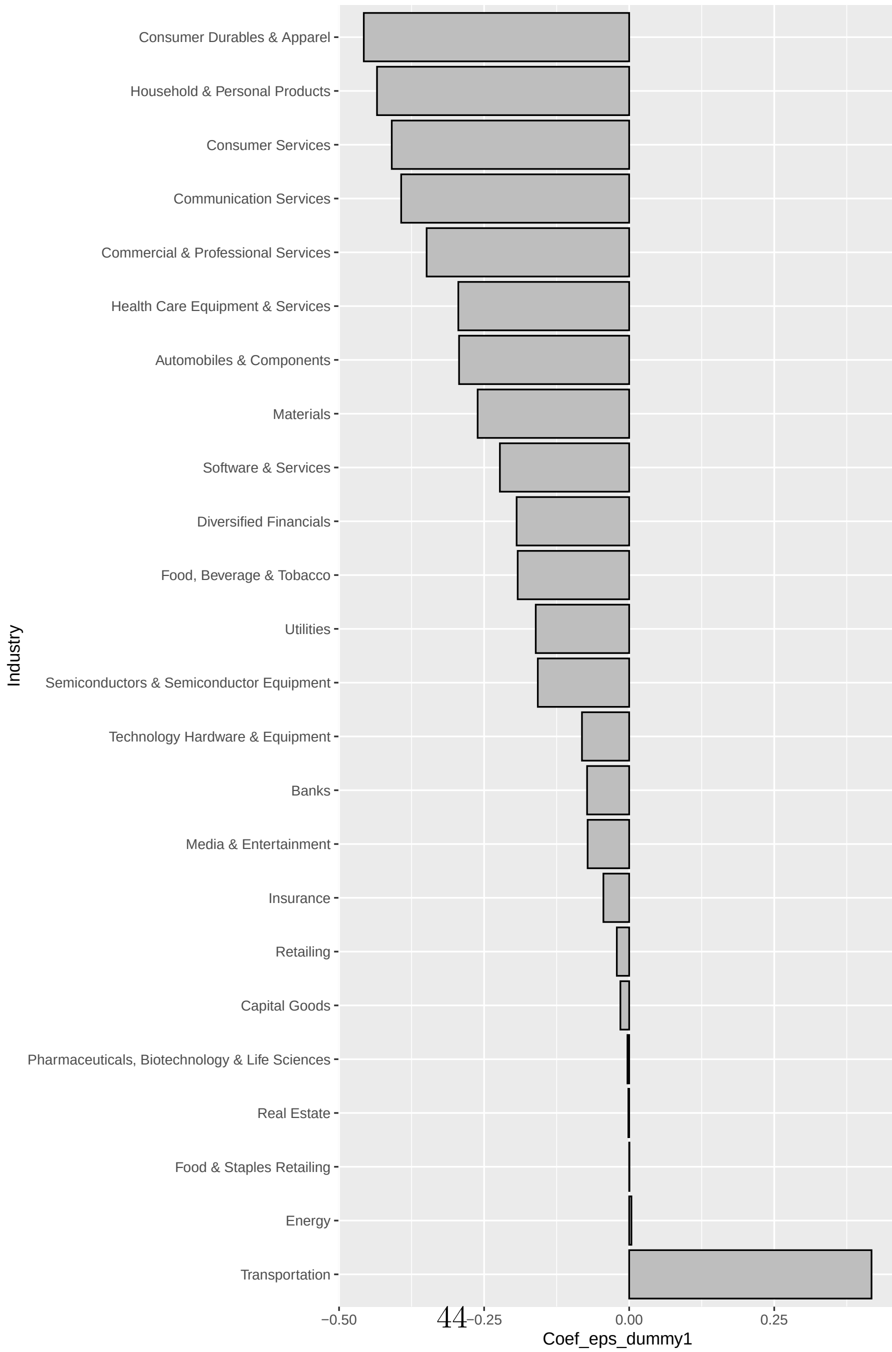


Figure 6: PTG sensitivity by industry

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

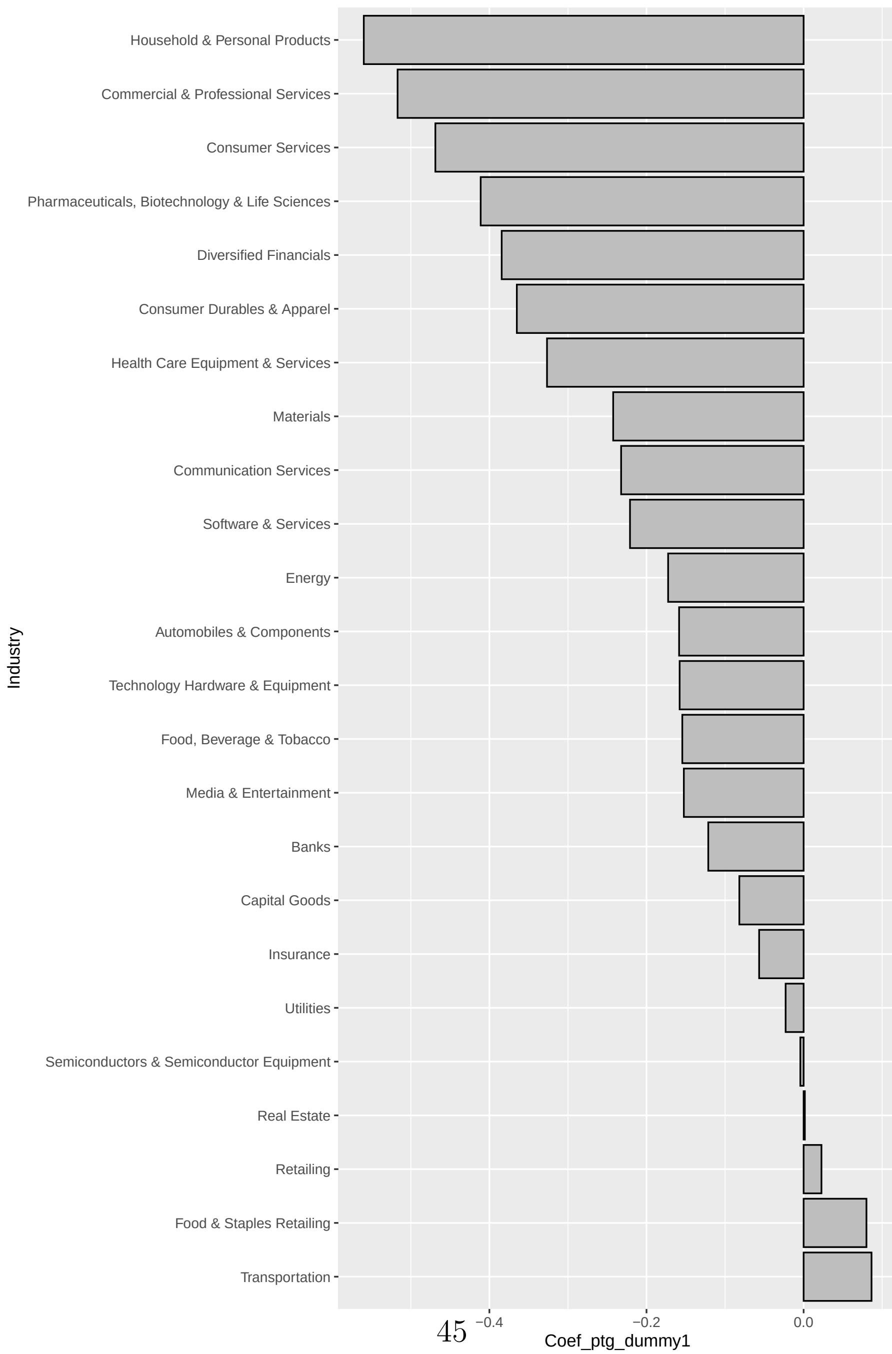
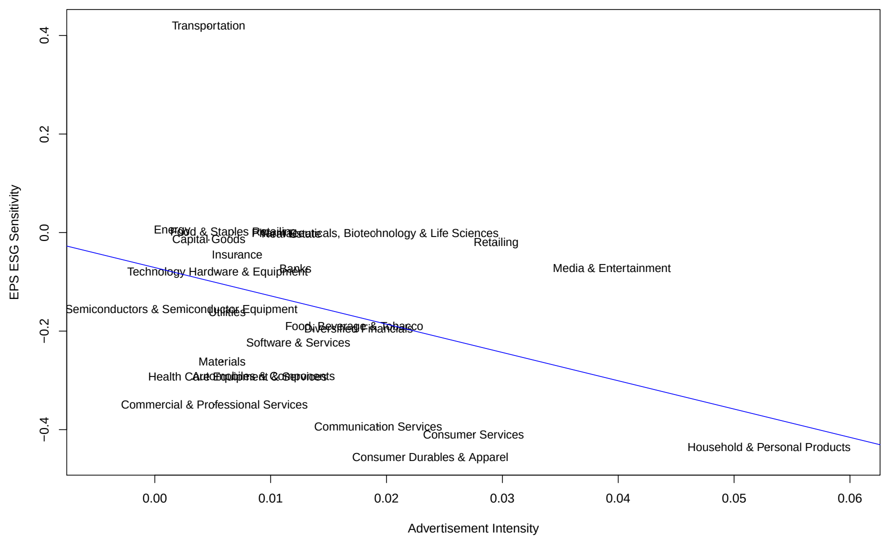


Figure 7: EPS sensitivity and Advertisement Intensity

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

(a) EPS Sensitivity



(b) PTG Sensitivity

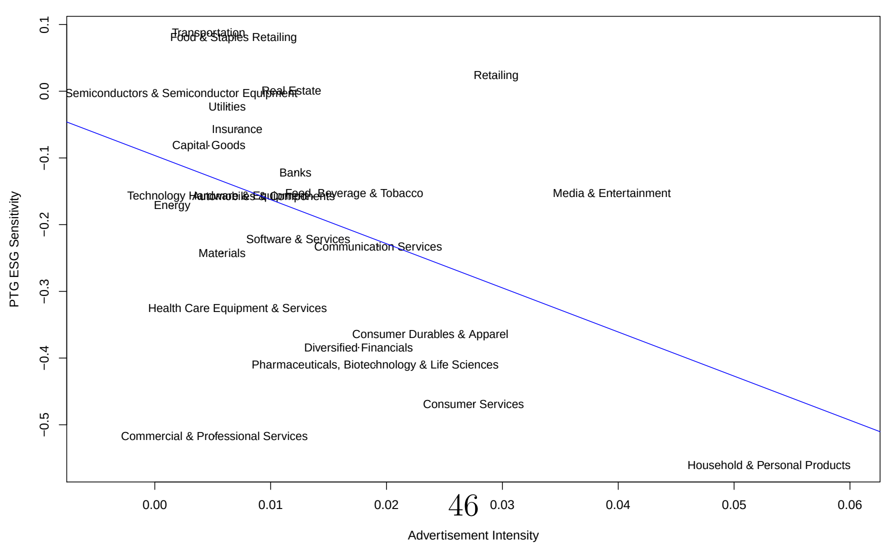
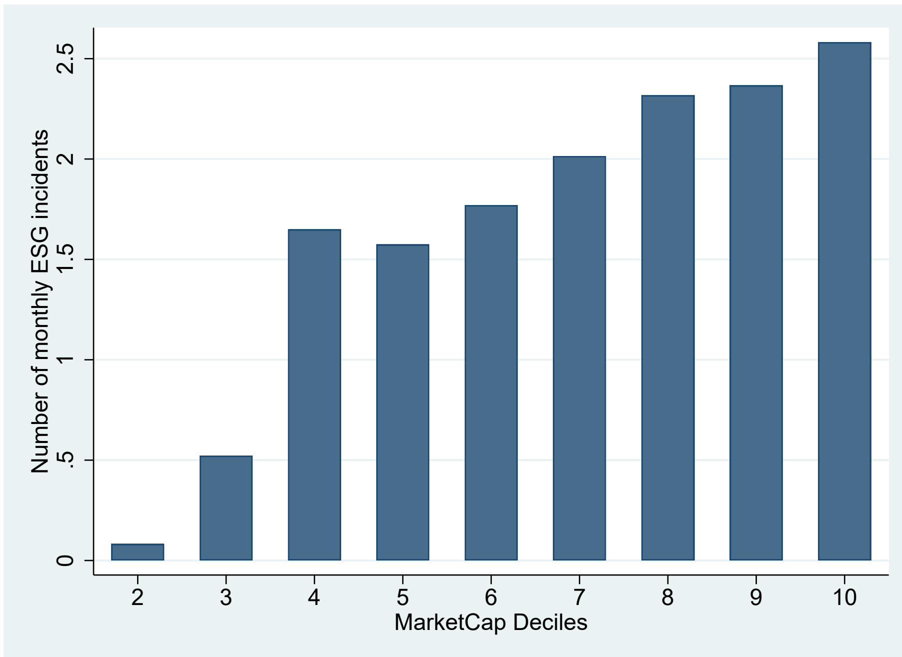


Figure 8: Number of incidents by size

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



Tables

Table 1: ESG incidents predict ESG scores

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

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

Table 2: Reaction of earnings forecast to ESG incidents

This table reports the results of regressing changes in consensus EPS forecast on ESG incidents. In columns (1) - (7), the dependent variables are changes of 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year ahead 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 forecasts. In column (8), the dependent variable is the change of the long-term growth forecast, defined as $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change of the price targets, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over the month t. In Panel A, the main independent variable takes on a value of one if at least one incident happens in months $[t-6, t]$, and zero otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happen in months $[t-6, t]$, 2 if more than 1 incident happen in months $[t-6, t]$, and 0 otherwise. Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.158***	-0.125**	-0.072	-0.065	-0.110***	-0.143***	-0.150***	-0.005	-0.170***	-0.167***
	(-2.72)	(-2.25)	(-1.30)	(-1.13)	(-2.97)	(-4.19)	(-4.02)	(-0.40)	(-7.74)	(-4.98)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.093	-0.059	0.010	-0.039	-0.069*	-0.101***	-0.113***	0.005	-0.133***	-0.160***
	(-1.47)	(-0.98)	(0.17)	(-0.62)	(-1.71)	(-2.77)	(-2.78)	(0.36)	(-5.65)	(-4.50)
>=2 incidents in the past 6 months	-0.302***	-0.273***	-0.253***	-0.125	-0.206***	-0.240***	-0.229***	-0.026	-0.254***	-0.184***
	(-3.72)	(-3.54)	(-3.35)	(-1.49)	(-3.97)	(-4.96)	(-4.46)	(-1.51)	(-8.04)	(-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	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table 3: Average term structure of EPS forecast

This table reports the results of regressing changes in the consensus EPS forecast at different horizons on changes in 1-year EPS forecast. In columns (1) - (6), the dependent variables are changes of 1-quarter, 2-quarter, 3-quarter, 4-quarter, 2-year, 3-year ahead 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 forecasts. In column (7), the dependent variable is the change of the long-term growth forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (8), the dependent variable is the change of the price targets, defined by $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (9), the dependent variable is the cumulative return over the month t. Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 2 year	(6) 3 year	(7) LTG	(8) PTG	(9) Return
1-year eps change	0.616***	0.506***	0.425***	0.306***	0.412***	0.255***	0.020***	0.154***	0.157***
	(120.16)	(96.12)	(77.97)	(34.82)	(125.69)	(71.05)	(18.41)	(77.40)	(59.86)
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	0.312	0.273	0.225	0.155	0.270	0.140	0.080	0.231	0.381
Obs.	271875	253030	233978	142399	542786	420445	196627	531519	548491

Table 4: Dividend Discount Model and Firm Valuation

This table reports the results of regressing several valuation-related variables on ESG incidents. In Column (1) and (2), the dependent variables are the level or ratio change in implied discount rate in month t. In Column (3), the dependent variable is the estimated change in firm value only through EPS change (in percentage points) in month t, defined in Section 4.2. In Column (4), the dependent variable is the cumulative return (in percentage points) over the month t. In Column (5), the dependent variable is the change of the price targets, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. The independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$, and 0 otherwise. The regression only uses the US sample. Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	$\Delta r_{i,t}$	$\frac{\Delta r_{i,t}}{r_{i,t-1}}$	$\frac{\widehat{\Delta PV_{i,t}}}{PV_{i,t-1}}$	$Ret.$	$\frac{\Delta PTG_{i,t}}{PTG_{i,t-1}}$
	(1)	(2)	(3)	(4)	(5)
>=1 incidents in the past 6 months=1	-0.000	-0.000	-0.188**	-0.108*	-0.169***
	(-0.09)	(-0.34)	(-2.39)	(-1.92)	(-4.47)
Month × Industry FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
adj R2	0.355	0.373	0.038	0.314	0.154
Obs.	164943	164943	164943	209587	192120

Table 5: Reaction of sales and gross margin forecasts to ESG incidents

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

Panel A: At least one incident

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
>=1 incidents in the past 6 months=1	-0.019	-0.037***	-0.040***	-0.021	-0.034***	-0.059***	-0.059***	-0.029*	-0.024	0.007	0.020	-0.019*	-0.018	0.002
	(-1.42)	(-2.70)	(-2.85)	(-1.44)	(-4.17)	(-6.25)	(-5.14)	(-1.71)	(-1.56)	(0.44)	(1.27)	(-1.72)	(-1.62)	(0.16)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.098	0.096	0.099	0.092	0.105	0.086	0.056	0.046	0.045	0.050	0.060	0.056	0.053
Obs.	279985	251644	224824	131232	552092	541921	417346	131259	119671	105483	61761	296492	286369	181832

Panel B: Number of incidents

	Sales							GrossMargin						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Q1	Q2	Q3	Q4	1 year	2 year	3 year	Q1	Q2	Q3	Q4	1 year	2 year	3 year
1 incident in the past 6 months	-0.005	-0.014	-0.013	-0.015	-0.025***	-0.041***	-0.038***	-0.033*	-0.019	0.017	0.020	-0.022*	-0.016	0.010
	(-0.37)	(-0.94)	(-0.83)	(-0.92)	(-2.79)	(-4.05)	(-2.96)	(-1.87)	(-1.12)	(1.00)	(1.20)	(-1.88)	(-1.38)	(0.68)
>=2 incidents in the past 6 months	-0.048***	-0.087***	-0.101***	-0.036*	-0.055***	-0.100***	-0.105***	-0.018	-0.037*	-0.015	0.019	-0.012	-0.021	-0.015
	(-2.62)	(-4.66)	(-5.29)	(-1.76)	(-4.88)	(-7.57)	(-6.82)	(-0.76)	(-1.69)	(-0.67)	(0.85)	(-0.75)	(-1.30)	(-0.78)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.098	0.096	0.099	0.092	0.105	0.086	0.056	0.046	0.045	0.050	0.060	0.056	0.053
Obs.	279985	251644	224824	131232	552092	541921	417346	131259	119671	105483	61761	296492	286369	181832

Table 6: Variation across Regions

This table reports the results of regressing changes in consensus EPS and sales forecasts on ESG incidents, interacted with dummy indicating regions. In Panel A columns (1) - (3), the dependent variables are changes of 1-year, 2-year, and 3-year ahead 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 of the long-term growth forecast, defined as $(LTG_t - LTG_{t-1}) \times 100$. In column (5), the dependent variable is the change of the consensus price target, 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 of 1-year, 2-year, and 3-year ahead 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 a dummy indicating firms in North America (US and Canada). $EU15$, *Asia* and *Others* are dummies indicating whether the firm is among the 15 most developed European countries (defined in Section 6.1), in Asia and in other regions (mostly Australia, Africa and South America). Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: EPS/PTG forecast

	(1) 1 year	(2) 2 year	(3) 3 year	(4) LTG	(5) PTG	(6) Return
>=1 incidents in the past 6 months=1	-0.087	-0.126**	-0.236***	-0.009	-0.179***	-0.113**
	(-1.61)	(-2.46)	(-3.88)	(-0.66)	(-5.13)	(-2.05)
>=1 incidents in the past 6 months=1 × EU15	-0.090	-0.110	0.103	0.028	-0.061	-0.193**
	(-0.91)	(-1.24)	(1.05)	(0.69)	(-0.95)	(-1.98)
>=1 incidents in the past 6 months=1 × Asia	-0.062	-0.051	0.149*	-0.003	-0.011	-0.092
	(-0.73)	(-0.65)	(1.74)	(-0.08)	(-0.21)	(-1.14)
>=1 incidents in the past 6 months=1 × Others	0.060	0.104	0.204*	-0.015	0.115	-0.037
	(0.50)	(0.97)	(1.81)	(-0.30)	(1.63)	(-0.35)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
adj R2	0.075	0.091	0.071	0.073	0.174	0.363
Obs.	561492	559144	432938	202190	575070	567951

Panel B: Sales forecast

	(1) 1 year	(2) 2 year	(3) 3 year
>=1 incidents in the past 6 months=1	-0.027**	-0.056***	-0.073***
	(-2.12)	(-3.83)	(-3.80)
>=1 incidents in the past 6 months=1 × EU15	-0.001	-0.025	-0.004
	(-0.03)	(-1.01)	(-0.14)
>=1 incidents in the past 6 months=1 × Asia	-0.015	0.004	0.060**
	(-0.79)	(0.16)	(2.24)
>=1 incidents in the past 6 months=1 × Others	-0.021	-0.003	-0.024
	(-0.71)	(-0.08)	(-0.58)
Month × Industry × Country FE	YES	YES	YES
Firm FE	YES	YES	YES
adj R2	0.092	0.105	0.086
Obs.	552092	541921	417346

Table 7: Interaction with Advertisement Intensity

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

Panel A: EPS/PTG forecast

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.103	-0.040	-0.016	-0.110	-0.030	-0.074	-0.147***	-0.011	-0.135***	-0.122***
	(-1.20)	(-0.47)	(-0.18)	(-1.21)	(-0.53)	(-1.44)	(-2.63)	(-0.54)	(-4.51)	(-2.66)
>=1 incidents in the past 6 months=1 × High Ad Intensity	-0.124	-0.172	-0.105	0.094	-0.178**	-0.152**	-0.002	0.008	-0.090**	-0.111*
	(-1.09)	(-1.57)	(-0.96)	(0.82)	(-2.49)	(-2.29)	(-0.02)	(0.29)	(-2.06)	(-1.67)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.088	0.089	0.083	0.093	0.075	0.091	0.071	0.073	0.174	0.363
Obs.	282989	262602	242214	147308	561492	559144	432938	202190	575070	567951

Panel B: Sales forecast

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
>=1 incidents in the past 6 months=1	0.009	-0.014	-0.020	0.019	-0.014	-0.041***	-0.035**
	(0.43)	(-0.61)	(-0.86)	(0.78)	(-1.15)	(-2.93)	(-2.08)
>=1 incidents in the past 6 months=1 × High Ad Intensity	-0.055**	-0.046*	-0.040	-0.078**	-0.042***	-0.038**	-0.051**
	(-2.11)	(-1.70)	(-1.40)	(-2.57)	(-2.64)	(-2.04)	(-2.22)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.098	0.096	0.099	0.092	0.105	0.086
Obs.	279985	251644	224824	131232	552092	541921	417346

Table 8: Interaction with Firm Size

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

Panel A: EPS/PTG forecast

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.223**	-0.168*	-0.184*	-0.193*	-0.240***	-0.248***	-0.246***	-0.034	-0.241***	-0.228***
	(-2.13)	(-1.71)	(-1.84)	(-1.76)	(-3.94)	(-4.35)	(-3.67)	(-1.23)	(-7.02)	(-4.33)
>=1 incidents in the past 6 months=1 × LargeFirm	0.102	0.073	0.188*	0.204	0.235***	0.189***	0.164**	0.033	0.119***	0.092
	(0.85)	(0.65)	(1.67)	(1.61)	(3.39)	(2.91)	(2.22)	(1.13)	(2.83)	(1.44)
LargeFirm	0.703***	0.742***	0.635***	0.534***	0.691***	0.737***	0.698***	0.031	0.582***	-1.385***
	(6.80)	(7.58)	(6.70)	(5.02)	(11.53)	(12.57)	(10.55)	(1.33)	(14.10)	(-20.59)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.088	0.090	0.084	0.093	0.075	0.092	0.072	0.073	0.175	0.364
Obs.	282988	262599	242214	147308	561484	559135	432934	202190	575066	567948

Panel A: Sales forecast

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year
>=1 incidents in the past 6 months=1	-0.022	-0.036	-0.047**	-0.052**	-0.041***	-0.081***	-0.069***
	(-1.04)	(-1.63)	(-2.05)	(-2.14)	(-3.21)	(-5.32)	(-3.67)
>=1 incidents in the past 6 months=1 × LargeFirm	0.006	-0.002	0.011	0.048*	0.013	0.040**	0.017
	(0.22)	(-0.07)	(0.39)	(1.75)	(0.87)	(2.21)	(0.78)
LargeFirm	0.111***	0.126***	0.134***	0.050**	0.086***	0.156***	0.171***
	(5.01)	(5.67)	(5.61)	(1.96)	(6.25)	(9.58)	(8.67)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
adj R2	0.095	0.099	0.096	0.099	0.092	0.105	0.086
Obs.	279984	251641	224824	131232	552051	541893	417344

Table 9: ESG sensitivity and forecast precision

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

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

Internet Appendix

Table IA1: List of ESG issues

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

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

Table IA2: Distribution of ESG incidents by types

This tables reports the distribution of ESG incidents by types. E, S and G indicates environment, social, and governance incidents respectively.

E	S	G	Percent
1	0	0	4.48
0	1	0	34.39
0	0	1	9.07
1	0	1	0.51
1	1	0	17.71
0	1	1	28.66
1	1	1	0.05

Table IA3: Distribution of observations across countries

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

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

Table IA4: Reaction of earnings forecast to ESG incidents - using different lags

This table reports the results of regressing changes in EPS forecast on ESG incidents. In columns (1) - (7), the dependent variables are changes of 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, 3-year ahead 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 forecasts. In column (8), the dependent variable is the change of the long-term growth forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change of the price targets, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over the month t. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-3, t]$, and 0 otherwise. In Panel B, the independent variable is defined as 1 if at least one incident happens in months $[t-9, t]$, and 0 otherwise. In Panel C, the independent variable is defined as 1 if at least one incident happens in months $[t-12, t]$, and 0 otherwise. Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Incidents with 3 months lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 3 months=1	-0.102*	-0.136**	-0.076	0.013	-0.136***	-0.134***	-0.153***	-0.013	-0.157***	-0.205***
	(-1.71)	(-2.34)	(-1.28)	(0.21)	(-3.46)	(-3.70)	(-3.91)	(-0.99)	(-6.76)	(-5.70)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Incidents with 9 months lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 9 months=1	-0.101*	-0.116**	-0.052	-0.041	-0.134***	-0.155***	-0.175***	-0.014	-0.165***	-0.185***
	(-1.73)	(-2.13)	(-0.94)	(-0.71)	(-3.74)	(-4.74)	(-4.65)	(-1.13)	(-7.62)	(-5.61)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Incidents with 12 months lag

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 12 months=1	-0.060	-0.120**	-0.021	0.005	-0.130***	-0.155***	-0.173***	-0.011	-0.168***	-0.171***
	(-1.03)	(-2.18)	(-0.38)	(0.10)	(-3.70)	(-4.75)	(-4.62)	(-0.84)	(-7.87)	(-5.15)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA5: Reaction of earnings forecast to ESG incidents - clustered by firm

This table reports the results of regressing changes in consensus EPS forecast on ESG incidents. In columns (1) - (7), the dependent variables are changes of 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year ahead 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 forecasts. In column (8), the dependent variable is the change of the long-term growth forecast, defined as $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change of the price targets, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over the month t. In Panel A, the main independent variable takes on a value of one if at least one incident happens in months $[t-6, t]$, and zero otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happen in months $[t-6, t]$, 2 if more than 1 incident happen in months $[t-6, t]$, and 0 otherwise. Standard errors are clustered at the firm level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.158**	-0.125*	-0.072	-0.065	-0.110**	-0.143***	-0.150***	-0.005	-0.170***	-0.167***
	(-2.25)	(-1.94)	(-1.12)	(-1.13)	(-2.50)	(-3.58)	(-3.92)	(-0.44)	(-6.46)	(-5.09)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.093	-0.059	0.010	-0.039	-0.069	-0.101**	-0.113***	0.005	-0.133***	-0.160***
	(-1.27)	(-0.87)	(0.15)	(-0.62)	(-1.50)	(-2.47)	(-2.81)	(0.39)	(-4.82)	(-4.49)
>=2 incidents in the past 6 months	-0.302***	-0.273***	-0.253***	-0.125	-0.206***	-0.240***	-0.229***	-0.026	-0.254***	-0.184***
	(-3.03)	(-2.91)	(-2.75)	(-1.44)	(-3.20)	(-4.04)	(-4.11)	(-1.64)	(-6.67)	(-3.95)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA6: Reaction of earnings forecast to ESG incidents - with time-varying controls

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

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.138**	-0.108*	-0.058	-0.054	-0.102***	-0.130***	-0.144***	-0.005	-0.161***	-0.170***
	(-2.38)	(-1.94)	(-1.04)	(-0.93)	(-2.78)	(-3.81)	(-3.88)	(-0.43)	(-7.38)	(-5.05)
Quintile MarketCap=2	0.514***	0.611***	0.510***	0.315***	0.522***	0.511***	0.601***	0.059**	0.418***	-1.506***
	(4.44)	(5.83)	(5.10)	(2.98)	(5.57)	(5.54)	(5.65)	(2.36)	(6.42)	(-14.06)
Quintile MarketCap=3	-0.029	0.463	0.433	0.861***	0.658***	0.538***	1.071***	0.028	0.696***	-2.363***
	(-0.09)	(1.44)	(1.44)	(2.68)	(3.46)	(2.85)	(5.03)	(0.46)	(6.25)	(-12.40)
Quintile MarketCap=4	1.101***	1.352***	1.321***	2.386***	1.505***	1.242***	1.534***	0.037	1.172***	-3.404***
	(2.65)	(3.19)	(2.94)	(4.79)	(7.02)	(5.73)	(6.41)	(0.47)	(8.95)	(-15.08)
Quintile MarketCap=5	1.458***	1.909***	1.419***	3.138***	2.242***	1.846***	1.939***	-0.020	1.684***	-4.550***
	(2.85)	(3.59)	(2.64)	(5.13)	(9.07)	(7.71)	(7.25)	(-0.21)	(11.04)	(-17.67)
Quintile B/M Ratio=2	-0.780***	-0.907***	-0.810***	-0.664**	-1.356***	-1.416***	-1.083***	-0.010	-0.850***	0.467***
	(-3.61)	(-4.05)	(-3.67)	(-2.47)	(-14.45)	(-14.94)	(-11.42)	(-0.25)	(-15.19)	(5.42)
Quintile B/M Ratio=3	-0.547*	-0.714**	-0.169	-0.203	-1.646***	-1.717***	-1.154***	0.013	-1.258***	0.585***
	(-1.84)	(-2.50)	(-0.59)	(-0.60)	(-11.35)	(-12.16)	(-7.32)	(0.20)	(-14.84)	(4.40)
Quintile B/M Ratio=4	-0.697***	-0.607***	-0.486**	-0.486**	-1.700***	-1.537***	-1.177***	-0.037	-1.384***	0.779***
	(-3.15)	(-2.79)	(-2.31)	(-2.19)	(-10.02)	(-9.21)	(-6.17)	(-0.70)	(-13.24)	(4.75)
Quintile B/M Ratio=5	-2.257***	-2.035***	-1.705***	-1.342***	-3.022***	-2.944***	-2.229***	-0.019	-2.385***	1.575***
	(-9.45)	(-8.81)	(-7.54)	(-5.70)	(-16.35)	(-16.06)	(-10.80)	(-0.34)	(-20.69)	(8.32)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.092	0.087	0.097	0.079	0.096	0.075	0.073	0.178	0.366
Obs.	278760	259008	239098	145417	546317	544152	420869	199237	559192	552951

Panel B: Number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.088	-0.053	0.013	-0.037	-0.070*	-0.095***	-0.113***	0.005	-0.129***	-0.158***
	(-1.38)	(-0.88)	(0.22)	(-0.59)	(-1.74)	(-2.60)	(-2.79)	(0.36)	(-5.48)	(-4.44)
>=2 incidents in the past 6 months	-0.251***	-0.231***	-0.215***	-0.093	-0.179***	-0.210***	-0.211***	-0.027	-0.236***	-0.197***
	(-3.09)	(-2.98)	(-2.85)	(-1.11)	(-3.44)	(-4.38)	(-4.12)	(-1.56)	(-7.48)	(-4.09)
Quintile MarketCap=2	0.512***	0.609***	0.507***	0.314***	0.521***	0.510***	0.600***	0.059**	0.416***	-1.506***
	(4.42)	(5.81)	(5.08)	(2.97)	(5.56)	(5.52)	(5.63)	(2.35)	(6.40)	(-14.07)
Quintile MarketCap=3	-0.028	0.464	0.434	0.862***	0.658***	0.538***	1.072***	0.028	0.696***	-2.363***
	(-0.09)	(1.45)	(1.45)	(2.68)	(3.46)	(2.85)	(5.03)	(0.46)	(6.25)	(-12.40)
Quintile MarketCap=4	1.094***	1.344***	1.310***	2.383***	1.503***	1.239***	1.533***	0.036	1.170***	-3.405***
	(2.63)	(3.17)	(2.91)	(4.78)	(7.01)	(5.72)	(6.41)	(0.47)	(8.93)	(-15.09)
Quintile MarketCap=5	1.458***	1.909***	1.423***	3.139***	2.240***	1.843***	1.938***	-0.020	1.682***	-4.551***
	(2.85)	(3.59)	(2.64)	(5.14)	(9.06)	(7.70)	(7.25)	(-0.21)	(11.03)	(-17.68)
Quintile B/M Ratio=2	-0.779***	-0.906***	-0.808***	-0.664**	-1.356***	-1.416***	-1.082***	-0.010	-0.850***	0.467***
	(-3.60)	(-4.04)	(-3.66)	(-2.46)	(-14.44)	(-14.93)	(-11.41)	(-0.24)	(-15.18)	(5.43)
Quintile B/M Ratio=3	-0.547*	-0.714**	-0.169	-0.203	-1.646***	-1.717***	-1.153***	0.013	-1.258***	0.585***
	(-1.84)	(-2.50)	(-0.59)	(-0.60)	(-11.35)	(-12.15)	(-7.31)	(0.20)	(-14.84)	(4.40)
Quintile B/M Ratio=4	-0.696***	-0.606***	-0.484**	-0.485**	-1.699***	-1.536***	-1.176***	-0.036	-1.383***	0.779***
	(-3.14)	(-2.79)	(-2.30)	(-2.19)	(-10.01)	(-9.20)	(-6.16)	(-0.69)	(-13.23)	(4.75)
Quintile B/M Ratio=5	-2.254***	-2.032***	-1.701***	-1.342***	-3.020***	-2.942***	-2.226***	-0.018	-2.383***	1.575***
	(-9.43)	(-8.80)	(-7.52)	(-5.69)	(-16.35)	(-16.05)	(-10.78)	(-0.32)	(-20.68)	(8.33)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.092	0.087	0.097	0.079	0.096	0.075	0.073	0.178	0.366
Obs.	278760	259008	239098	145417	546317	544152	420869	199237	559192	552951

Table IA7: Reaction of earnings forecast to ESG incidents - no firm fixed effect

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

Panel A: At least one incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.358***	-0.196***	-0.132***	-0.169***	-0.310***	-0.252***	-0.220***	-0.011	-0.270***	-0.168***
	(-6.98)	(-4.06)	(-2.74)	(-3.29)	(-9.64)	(-8.47)	(-6.97)	(-1.08)	(-14.58)	(-5.34)
Quintile MarketCap=2	1.257***	1.034***	0.747***	0.326***	0.989***	0.861***	0.844***	0.052***	0.391***	0.061
	(21.61)	(20.25)	(14.84)	(6.50)	(22.68)	(20.34)	(14.97)	(4.46)	(13.05)	(1.12)
Quintile MarketCap=3	1.268***	1.236***	1.068***	0.731***	1.913***	1.616***	1.711***	0.089**	1.002***	0.731***
	(6.12)	(6.10)	(5.34)	(3.30)	(16.17)	(13.80)	(13.50)	(2.43)	(15.35)	(5.52)
Quintile MarketCap=4	2.520***	2.360***	1.945***	1.415***	2.871***	2.347***	2.276***	0.143***	1.404***	0.956***
	(9.93)	(9.41)	(7.49)	(4.50)	(21.81)	(18.14)	(16.59)	(3.26)	(19.17)	(6.40)
Quintile MarketCap=5	3.031***	2.850***	2.287***	1.861***	3.520***	2.884***	2.662***	0.139***	1.853***	1.112***
	(10.50)	(9.69)	(7.71)	(5.06)	(24.52)	(20.57)	(17.37)	(2.60)	(22.30)	(6.67)
Quintile B/M Ratio=2	-0.921***	-0.790***	-0.689***	-0.661***	-1.062***	-1.050***	-0.871***	-0.030	-0.666***	-0.072
	(-5.93)	(-5.02)	(-4.30)	(-3.38)	(-15.71)	(-15.37)	(-13.09)	(-1.07)	(-16.78)	(-1.12)
Quintile B/M Ratio=3	-0.648***	-0.603***	-0.138	0.093	-1.172***	-1.150***	-0.842***	-0.029	-1.002***	-0.311***
	(-3.26)	(-3.13)	(-0.70)	(0.39)	(-11.55)	(-11.80)	(-8.02)	(-0.61)	(-17.27)	(-3.23)
Quintile B/M Ratio=4	-0.076	0.044	0.115	0.127	-0.575***	-0.426***	-0.332***	-0.041	-0.678***	-0.041
	(-0.54)	(0.33)	(0.89)	(0.96)	(-5.23)	(-3.93)	(-2.69)	(-1.27)	(-9.63)	(-0.37)
Quintile B/M Ratio=5	-1.431***	-1.026***	-0.733***	-0.369***	-1.514***	-1.273***	-0.813***	-0.040	-1.423***	-0.068
	(-9.48)	(-7.43)	(-5.39)	(-2.69)	(-12.72)	(-10.68)	(-6.09)	(-1.20)	(-19.08)	(-0.55)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
adj R2	0.067	0.075	0.073	0.081	0.054	0.076	0.062	0.079	0.170	0.361
Obs.	278844	259080	239173	145643	546383	544202	420981	199335	559239	552995

Panel B: Number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.192***	-0.063	0.007	-0.112*	-0.196***	-0.171***	-0.151***	-0.002	-0.191***	-0.165***
	(-3.21)	(-1.12)	(0.12)	(-1.89)	(-5.16)	(-4.92)	(-3.94)	(-0.14)	(-8.74)	(-4.94)
>=2 incidents in the past 6 months	-0.515***	-0.320***	-0.260***	-0.222***	-0.423***	-0.334***	-0.284***	-0.019	-0.350***	-0.171***
	(-7.84)	(-5.17)	(-4.35)	(-3.36)	(-10.30)	(-8.80)	(-7.52)	(-1.53)	(-14.57)	(-4.01)
Quintile MarketCap=2	1.295***	1.064***	0.778***	0.339***	1.017***	0.881***	0.861***	0.054***	0.410***	0.062
	(22.16)	(20.76)	(15.37)	(6.73)	(23.21)	(20.75)	(15.32)	(4.60)	(13.55)	(1.13)
Quintile MarketCap=3	1.373***	1.324***	1.165***	0.773***	1.962***	1.652***	1.744***	0.096***	1.037***	0.732***
	(6.66)	(6.56)	(5.78)	(3.46)	(16.60)	(14.15)	(13.74)	(2.60)	(15.82)	(5.54)
Quintile MarketCap=4	2.656***	2.473***	2.070***	1.471***	2.948***	2.404***	2.327***	0.153***	1.458***	0.958***
	(10.59)	(9.97)	(7.95)	(4.71)	(22.43)	(18.63)	(16.90)	(3.44)	(19.74)	(6.45)
Quintile MarketCap=5	3.206***	2.992***	2.444***	1.930***	3.611***	2.951***	2.722***	0.151***	1.918***	1.114***
	(11.19)	(10.27)	(8.21)	(5.29)	(25.19)	(21.08)	(17.67)	(2.76)	(22.90)	(6.72)
Quintile B/M Ratio=2	-0.914***	-0.785***	-0.683***	-0.658***	-1.057***	-1.046***	-0.867***	-0.029	-0.663***	-0.072
	(-5.89)	(-4.98)	(-4.27)	(-3.37)	(-15.66)	(-15.34)	(-13.03)	(-1.04)	(-16.71)	(-1.12)
Quintile B/M Ratio=3	-0.648***	-0.605***	-0.141	0.091	-1.167***	-1.147***	-0.839***	-0.028	-0.998***	-0.311***
	(-3.26)	(-3.13)	(-0.72)	(0.38)	(-11.51)	(-11.77)	(-7.99)	(-0.60)	(-17.22)	(-3.23)
Quintile B/M Ratio=4	-0.074	0.045	0.116	0.127	-0.569***	-0.422***	-0.329***	-0.041	-0.674***	-0.041
	(-0.53)	(0.34)	(0.89)	(0.96)	(-5.19)	(-3.90)	(-2.66)	(-1.26)	(-9.58)	(-0.37)
Quintile B/M Ratio=5	-1.421***	-1.018***	-0.724***	-0.365***	-1.500***	-1.263***	-0.804***	-0.039	-1.413***	-0.068
	(-9.41)	(-7.37)	(-5.33)	(-2.67)	(-12.63)	(-10.61)	(-6.03)	(-1.17)	(-18.96)	(-0.54)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
adj R2	0.067	0.075	0.073	0.081	0.054	0.076	0.062	0.079	0.170	0.361
Obs.	278844	259080	239173	145643	546383	544202	420981	199335	559239	552995

Table IA8: Reaction of earnings forecast to ESG incidents - control fundamentals

This table reports the results of regressing changes in EPS forecast on ESG incidents. In columns (1) - (7), the dependent variables are changes of 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, 3-year ahead 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 forecasts. In column (8), the dependent variable is the change of the long-term growth forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change of the price targets, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over the month t. In Panel A, the independent variable is defined as 1 if at least one incident happens in months $[t-6, t]$, and 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 incident happen 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 $\Delta(\frac{NetDebt}{Asset})_t = (\frac{NetDebt}{Asset})_t - (\frac{NetDebt}{Asset})_{t-1}$. Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Any incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in the past 6 months=1	-0.178***	-0.102*	-0.062	-0.071	-0.085**	-0.135***	-0.163***	-0.015	-0.167***	-0.146***
	(-2.94)	(-1.76)	(-1.08)	(-1.19)	(-2.12)	(-3.65)	(-4.00)	(-1.09)	(-7.08)	(-4.04)
Δ ROA	1.792***	1.466***	1.204***	1.377***	1.641***	1.299***	0.868***	-0.507***	0.663***	0.694***
	(11.27)	(10.59)	(9.19)	(3.10)	(17.56)	(16.84)	(5.61)	(-15.37)	(13.29)	(10.44)
Δ CapEx/Asset	-0.078	0.136	0.205	0.489	0.157	0.081	0.180	0.016	-0.315***	-0.273**
	(-0.26)	(0.55)	(0.84)	(0.48)	(0.99)	(0.53)	(0.65)	(0.26)	(-3.51)	(-2.23)
Δ NetDebt/Asset	-0.154***	-0.109**	-0.049	-0.052	-0.097***	-0.080***	-0.088	-0.010	-0.115***	-0.125***
	(-2.76)	(-2.19)	(-1.06)	(-0.30)	(-3.22)	(-2.68)	(-1.63)	(-0.91)	(-6.03)	(-4.77)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.094	0.087	0.096	0.079	0.097	0.073	0.074	0.167	0.347
Obs.	257527	239940	222268	136370	476711	475173	364748	174307	485043	478838

Panel B: Number of incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 incident in the past 6 months	-0.113*	-0.043	0.010	-0.044	-0.043	-0.086**	-0.120***	-0.004	-0.127***	-0.139***
	(-1.71)	(-0.69)	(0.17)	(-0.68)	(-0.98)	(-2.16)	(-2.68)	(-0.28)	(-5.01)	(-3.60)
>=2 incidents in the past 6 months	-0.322***	-0.233***	-0.222***	-0.131	-0.183***	-0.246***	-0.254***	-0.037**	-0.260***	-0.162***
	(-3.80)	(-2.87)	(-2.84)	(-1.52)	(-3.25)	(-4.74)	(-4.57)	(-2.00)	(-7.57)	(-3.13)
Δ ROA	1.792***	1.466***	1.204***	1.376***	1.641***	1.298***	0.868***	-0.507***	0.663***	0.694***
	(11.27)	(10.59)	(9.19)	(3.10)	(17.56)	(16.84)	(5.62)	(-15.37)	(13.28)	(10.44)
Δ CapEx/Asset	-0.078	0.135	0.204	0.488	0.157	0.082	0.181	0.016	-0.315***	-0.273**
	(-0.26)	(0.55)	(0.84)	(0.48)	(1.00)	(0.54)	(0.66)	(0.26)	(-3.50)	(-2.23)
Δ NetDebt/Asset	-0.154***	-0.108**	-0.048	-0.052	-0.097***	-0.079***	-0.088	-0.010	-0.115***	-0.125***
	(-2.76)	(-2.18)	(-1.05)	(-0.30)	(-3.22)	(-2.67)	(-1.63)	(-0.90)	(-6.03)	(-4.77)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.091	0.094	0.087	0.096	0.079	0.097	0.073	0.074	0.167	0.347
Obs.	257527	239940	222268	136370	476711	475173	364748	174307	485043	478838

Table IA9: Reaction of earnings forecast to ESG incidents - by E/S/G

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

Panel A: Environmental incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 E incidents in the past 6 months=1	-0.141*	-0.047	-0.213***	-0.138	-0.065	-0.090*	-0.083	0.013	-0.093***	-0.091*
	(-1.73)	(-0.60)	(-2.74)	(-1.55)	(-1.28)	(-1.90)	(-1.63)	(0.79)	(-3.19)	(-1.95)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Social incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 S incidents in the past 6 months=1	-0.165***	-0.205***	-0.116**	-0.093	-0.164***	-0.191***	-0.168***	-0.005	-0.166***	-0.131***
	(-2.77)	(-3.62)	(-2.12)	(-1.56)	(-4.42)	(-5.47)	(-4.47)	(-0.37)	(-7.42)	(-3.87)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Governance incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 G incidents in the past 6 months=1	-0.127*	-0.038	0.012	0.017	-0.115***	-0.084**	-0.107**	-0.012	-0.137***	-0.137***
	(-1.87)	(-0.58)	(0.18)	(0.25)	(-2.60)	(-2.13)	(-2.57)	(-0.84)	(-5.13)	(-3.33)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA10: Reaction of earnings forecast to ESG incidents - by E/S/G

This table reports the results of regressing changes in EPS forecast on ESG incidents. In columns (1) - (7), the dependent variables are changes of 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, 3-year ahead 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 forecasts. In column (8), the dependent variable is the change of the long-term growth forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change of the price targets, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over the month t. In Panel A, the independent variable is defined as 1 if 1 environmental incidents happen in months $[t-6, t]$, 2 if more than 1 environmental incident happen in months $[t-6, t]$ and 0 otherwise. In Panel B, the independent variable is defined as 1 if 1 social incidents happen in months $[t-6, t]$, 2 if more than 1 social incident happen in months $[t-6, t]$ and 0 otherwise. In Panel C, the independent variable is defined as 1 if 1 governance incidents happen in months $[t-6, t]$, 2 if more than 1 governance incident happen in months $[t-6, t]$ and 0 otherwise. Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Environmental incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 E incident in the past 6 months	-0.071	0.017	-0.187**	-0.063	-0.049	-0.046	-0.064	0.029	-0.060*	-0.081*
	(-0.82)	(0.20)	(-2.24)	(-0.68)	(-0.88)	(-0.91)	(-1.17)	(1.64)	(-1.92)	(-1.66)
>=2 E incidents in the past 6 months	-0.319**	-0.209*	-0.279**	-0.325**	-0.109	-0.210***	-0.134*	-0.028	-0.186***	-0.121*
	(-2.51)	(-1.75)	(-2.34)	(-2.29)	(-1.41)	(-2.85)	(-1.72)	(-1.20)	(-4.17)	(-1.71)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Social incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 S incident in the past 6 months	-0.101	-0.136**	-0.034	-0.031	-0.121***	-0.152***	-0.141***	0.008	-0.134***	-0.131***
	(-1.55)	(-2.23)	(-0.58)	(-0.49)	(-3.02)	(-4.08)	(-3.49)	(0.56)	(-5.53)	(-3.63)
>=2 S incidents in the past 6 months	-0.308***	-0.355***	-0.296***	-0.228***	-0.260***	-0.277***	-0.224***	-0.030*	-0.238***	-0.131***
	(-3.59)	(-4.36)	(-3.75)	(-2.59)	(-4.85)	(-5.48)	(-4.19)	(-1.74)	(-7.40)	(-2.68)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Governance incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
1 G incident in the past 6 months	-0.088	0.019	0.054	0.050	-0.058	-0.050	-0.104**	-0.010	-0.133***	-0.174***
	(-1.19)	(0.27)	(0.79)	(0.66)	(-1.23)	(-1.17)	(-2.30)	(-0.62)	(-4.51)	(-3.86)
>=2 G incidents in the past 6 months	-0.222**	-0.173*	-0.089	-0.060	-0.252***	-0.166***	-0.116**	-0.018	-0.148***	-0.051
	(-2.18)	(-1.77)	(-0.93)	(-0.60)	(-3.91)	(-2.88)	(-1.99)	(-0.85)	(-3.84)	(-0.85)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Table IA11: Reaction of earnings forecast to ESG incidents - by novelty, reach and severity

This table reports the results of regressing changes in EPS forecast on ESG incidents. In columns (1) - (7), the dependent variables are changes of 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, 3-year ahead 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 forecasts. In column (8), the dependent variable is the change of the long-term growth forecast, defined by $(LTG_t - LTG_{t-1}) \times 100$. In column (9), the dependent variable is the change of the price targets, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over the month t. In Panel A, the independent variable is defined as 1 if any novel incidents happen in months $[t-6, t]$, and 0 otherwise. In Panel B, the independent variable is defined as 1 if any reach incidents happen in months $[t-6, t]$, and 0 otherwise. In Panel C, the independent variable is defined as 1 if any severe incidents happen in months $[t-6, t]$, and 0 otherwise. Novel, reach and severe incidents are defined as those with Reprisk novelty, reach and severity measures are equal or larger than 2. Standard errors are clustered at the industry-month level. t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A: Novel incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 novel incidents in the past 6 months=1	-0.118**	-0.117**	-0.087	-0.064	-0.096***	-0.137***	-0.150***	-0.016	-0.166***	-0.144***
	(-2.06)	(-2.05)	(-1.57)	(-1.10)	(-2.62)	(-4.01)	(-4.03)	(-1.30)	(-7.60)	(-4.26)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel B: Reach incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 reach incidents in the past 6 months=1	-0.246***	-0.141**	-0.082	-0.091	-0.148***	-0.184***	-0.156***	-0.016	-0.166***	-0.151***
	(-3.92)	(-2.42)	(-1.39)	(-1.38)	(-3.84)	(-5.12)	(-4.15)	(-1.24)	(-7.22)	(-4.26)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966

Panel C: Severe incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) 1 year	(6) 2 year	(7) 3 year	(8) LTG	(9) PTG	(10) Ret.
>=1 severe incidents in the past 6 months=1	-0.174**	-0.185***	-0.197***	-0.221***	-0.195***	-0.178***	-0.143***	-0.006	-0.156***	-0.115***
	(-2.49)	(-2.75)	(-3.04)	(-3.25)	(-4.40)	(-4.21)	(-3.23)	(-0.41)	(-5.77)	(-2.77)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
adj R2	0.089	0.090	0.085	0.095	0.077	0.093	0.073	0.073	0.176	0.364
Obs.	279530	259734	239787	145738	548322	546116	421821	199753	561343	554966