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ESG News, Future Cash Flows, and Firm Value

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ABSTRACT

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

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

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While ESG has received increasing attention among both practitioners and academics (see, e.g., Gillan, Koch, and Starks (2021) for a survey), the extent to which ESG information impacts firm value is still widely debated. In addition, the channels–if any–through which ESG information affects firm value are poorly understood.

One channel through which ESG information might affect firm value relates to the impact of divestment on firms' cost of capital. If firms with poor ESG reputations are shunned or underweighted by a sufficiently large pool of investors, their cost of capital should be higher, and hence, firm values should be lower. Such a *discount rate* channel has been modeled by Heinkel, Kraus, and Zechner (2001) and Pástor, Stambaugh, and Taylor (2021), and empirically tested by Hong and Kacperczyk (2009), Luo and Balvers (2017), and Bolton and Kacperczyk (2021). ESG may also affect stock market values if ESG metrics predict a firm's future earnings. For instance, if a firm is subject to negative ESG news, such as the revelation of unexpectedly high levels of pollution, shareholders might revise earnings forecasts downward due to binding regulatory constraints, potential liabilities, or negative reactions from customers. Such real implications of ESG information for firm earnings might be either short-lived (e.g., through a fine or the settlement of a lawsuit) or persistent, for instance, because customers or employees turn their back on firms with poor ESG profiles or because the firm's production technology cannot be changed rapidly. If some investors are unaware of the importance of ESG information for future earnings, such information might predict both contemporaneous and future stock returns. This *cash flow* channel is modeled in Pedersen, Fitzgibbons, and Pomorski (2021), and evidence of investor underreaction is provided, for instance, in Edmans (2011) and Gloßner (2021).

The main goal of our study is to investigate the cash flow channel. To do so, we consider earnings forecasts made by security analysts and ask how forecasted earnings change following negative ESG news. Does negative ESG news affect forecasts at all horizons equally, or are analyst reactions, for instance, weaker at short horizons (one quarter) and stronger at longer horizons (three years)? Also of interest is the mechanism through which analysts believe negative ESG news affects earnings. For example, we explore whether changes in earnings forecasts are due to changes in expected sales or expected margins? We also ask if analysts should react to negative ESG news, or if forecasts would be more accurate when ignoring such news events.

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

We use ESG news data rather than ESG ratings (or scores) for multiple reasons. First, doing so allows us to avoid the well-documented inconsistency of ESG ratings. For instance, Gibson-Brandon, Krueger, and Schmidt (2021) and

Berg, Koelbel, and Rigobon (2022) document disagreement in the ESG ratings issued by different data providers. In addition, Berg, Fabisik, and Sautner (2021) document backfilling issues in the Refinitiv ESG data, a widely used ESG data set. Besides these methodological issues, another concern with using ESG ratings is that they tend to move slowly and for reasons that are not always clear. They can change, for example, following a periodic (e.g., annual) rating revision by the rating provider, the release of new ESG information by firms through ESG/sustainability reports, ratings changes at peer firms, changes in rating methodologies, etc. Berg, Heeb, and Kölbel (2024) find that ESG fund ownership reacts to changes in MSCI ESG ratings, but the reaction is slow, over a period of up to two years, which suggests that the reaction comes from compliance instead of information about fundamentals. In contrast, ESG news events provide cleanly identifiable shocks to a firm's ESG characteristics and fundamentals, which are more suitable to study analyst forecast revisions.

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

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

We also study the heterogeneity in our main results by industry, firm size, and geography. We find that the ESG forecast revision effect is stronger for smaller firms. It is somewhat stronger for firms in business-to-consumer (B2C) industries, but it does not vary much across regions.

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

As explained above, ESG might affect firm value through a cash flow channel or a discount rate channel. While the main objective of our paper is to shed light on the importance of the cash flow channel, we also evaluate the relative importance of both channels in driving stock market values following negative ESG events. Using a simple dividend discount approach, we decompose negative ESG news-induced changes in firm value in a component coming from changes in cash flow expectations and a component coming from changes in discount rates. Our analysis shows that changes in earnings forecasts can account for most of the negative response of firm valuations following ESG incidents, while we do not find significant changes in implied discount rates. This is in line with the conclusions of Berk and van Binsbergen (2024), who argue theoretically that ESG divestment has no detectable effect on firms' cost of capital. Empirically, Lindsey, Pruitt, and Schiller (2024) show that ESG scores do not convey novel information about systematic risk beyond what is already known from other firm characteristics (e.g., quality, volatility, etc.). Our findings are also consistent with recent papers showing that a large fraction of medium-term stock price movements can be attributed to changes in earnings expectations (Engelberg, McLean, and Pontiff (2018), Lochstoer and Tetlock (2020), De-La-O and Myers (2021)) rather than changes in discount rates. One caveat of our discount rate analysis is that the tests may lack statistical power, and thus, we cannot rule out the possibility that the discount rate channel is also at play. Notwithstanding, overall our evidence suggests that, quantitatively, the decline in firm value following negative ESG news results from changes in expected cash flows.

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

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

Another stream of the literature focuses on the cost of capital by examining the effect of ESG policies on measures of (systematic) risk. Dunn, Fitzgibbons, and Pomorski (2018) and Albuquerque, Koskinen, and Zhang (2019), for instance, provide evidence that better ESG policies are associated with lower systematic risk. More recently, Lindsey, Pruitt, and Schiller (2024) construct a rich data set using ESG scores from seven major ESG data providers and combine these ESG scores with a large set of other stock characteristics (see Jensen, Kelly, and Pedersen (2023)). Contrary to some prior studies, they conclude that when controlling for a substantial amount of the conditioning information that investors have at their disposal, ESG measures do not convey novel information about systematic risk.

Our paper is also related to a series of recent papers that use RepRisk data. For instance, Akey et al. (2024) show that reputation-related Reprisk incidents negatively affect firm value. Related to our work are also two other papers that use RepRisk data but with different focuses. Gantchev, Giannetti, and Li (2022) document divesting by responsible investors following negative environmental and social incidents. They show that firms owned by more responsible shareholders experience larger temporary declines in valuations and react by subsequently improving their ESG performance. Also using RepRisk data, Gloßner (2021) focuses mainly on how the stock market processes negative ESG information and finds that negative shocks predict negative future stock returns, suggesting underreaction to such information in the stock markets.

The paper is organized as follows. Section I describes the data. Section II presents the results on analysts' reaction to ESG incidents. Section III investigates the economic mechanisms. Section IV disentangles the cash flow versus discount rate channel. Section V explores the heterogeneity of the impact of ESG incidents. Section VI discusses whether analysts are correct in adjusting the forecasts. Finally, Section VII concludes.

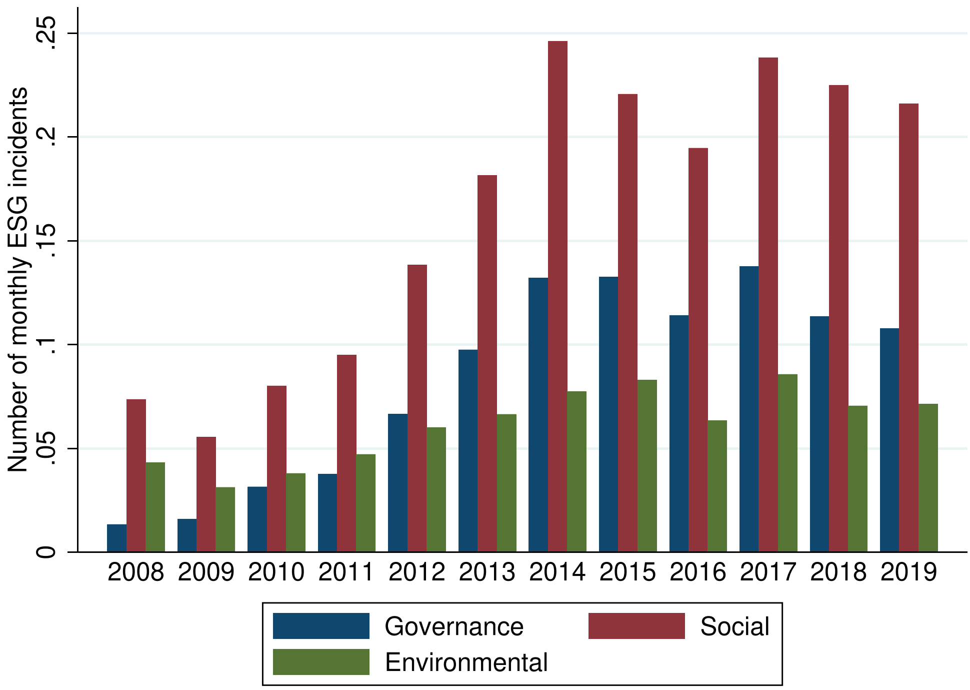


Figure 1. Number of RepRisk ESG incidents by year. This figure shows the average number of monthly environmental, social, and governance incidents per firm by year. Green, red, and blue bars represent environmental, social, and governance incidents, respectively. (Color figure can be viewed at wileyonlinelibrary.com)

I. Data

A. RepRisk and Other ESG Scores

Our main ESG data come from RepRisk. RepRisk produces daily indicators for negative ESG-related incidents at the firm level. It does so through a daily analysis of a large set of documents in 20 languages obtained from public sources. The data go back to January 2007, with daily granularity. RepRisk classifies ESG incidents according to 28 distinct issues. Environmental (E) issues include news about, for example, climate change, pollution, and waste issues. Social (S) issues include, for example, child labor and human rights abuses. Governance (G) issues capture issues such as executive compensation and corruption. Panel A of Table I reports the full list of issues and Panel B presents the distribution of E, S, and G incidents. Approximately half of the incidents are associated with two or more E, S, and G categories (Panel B). Events related to social issues are the most frequent in the RepRisk data. Figure 1 reports the average number of monthly E, S, and G incidents per firm by year. The number of ESG incidents recorded by RepRisk has increased

Table I

Descriptive Statistics of RepRisk Data

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

Panel A: List of ESG Issues

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

Panel B: Distribution of Environmental, Social, and Governance Incidents

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

Panel C: Distribution of Novelty, Severity, and Reach Levels

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

over time. At the beginning of the sample period, there are more environmental than governance incidents, while at the end of the sample period, there are more governance incidents. In addition, RepRisk categorizes ESG incidents based on their novelty, reach, and severity. The novelty, reach, and severity of incidents are measured on a scale from 1 to 3, where 3 represents the most novel, most influential, or most severe incidents. Panel C of Table I shows the distribution of novelty, reach, and severity levels. No incidents are labeled as novelty-3 incidents and only 1% of incidents are labeled as severity-3 incidents. Internet Appendix Table IA.I lists illustrative examples of RepRisk incidents.[1] For instance, Microsoft was criticized for sourcing cobalt from the Democratic Republic of Congo, which involved child labor and human rights abuses, and Chinese solar company JinkoSolar was accused of water pollution, which led to protests by local residents.

RepRisk prides itself with supplying distinct data compared to traditional ESG ratings, as Reprisk data are based primarily on news. The news captures the negative impacts that firms have on the environment (e.g., greenhouse gas emissions, toxic releases), workers (e.g., workplace accidents), or communities (e.g., tax evasion). As RepRisk incidents are observable outcomes of firms' ESG policies, they reflect (at least partially) firms' ESG processes.[2] As such, they are signals about the quality of firms' ESG practices and, more generally, about their ESG policies.

To confirm that RepRisk incidents provide information about firms' ESG practices, we explore the relation between RepRisk incidents and the ESG scores used in existing ESG literature. We use ESG scores from Refinitiv (previously Asset4),[3] Morningstar Sustainalytics (hereafter Sustainalytics), and MSCI. We create a monthly panel using the three scores. We adjust all the scores to a 0 to 100 scale to make them comparable. We match RepRisk with these data sets through International Securities Identification Numbers (ISINs). In the Appendix, we show that a strong and significantly negative relation exists between ESG events and subsequent ESG ratings. The latter finding justifies our use of ESG incidents as negative shocks to the ESG profiles of firms.

B. IBES

We collect monthly analyst consensus forecasts of earnings per share (EPS), sales, gross margins (reported in percentage points), long-term growth (LTG), and price targets (PTGs) from IBES. EPS, sales, and gross margin forecasts are issued over one-quarter, two-quarter, three-quarter, four-quarter, one-year,

[1] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

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

[3] We use Refinitiv scores despite the time-inconsistency issue mentioned in Berg, Fabisik, and Sautner (2021) because these scores are widely used in the ESG literature.

two-year, and three-year horizons. We use forecasts only up to three years because the forecasts for longer horizons are missing for a large subset of firms. The LTG forecast from IBES represents the expected annual rate of growth in operating earnings over the company's next full business cycle. In general, LTG forecasts refer to a period of between three and five years. The PTGs from IBES represent the projected price level within a specific time horizon forecasted by the analysts. We restrict our sample to PTGs for 12 months.

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

C. Stock Returns, Fundamentals, and Other Events

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

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

We complement our matched data set with event data from the Capital IQ Key Developments database, which provides structured summaries of material news and events for companies worldwide. The events retained in the Capital IQ Key Developments data set are related to issues such as executive changes, mergers and acquisitions (M&A) rumors, Securities and Exchange

Commission (SEC) inquiries, and many more. We use event dates and event types, and we merge the key development data with our main data through ISINs.

D. Construction of Key Variables

Our analysis focuses on changes in forecasts. For EPS forecast F_tEPS_{t+h} made in month t for horizon h, we define the change in EPS forecasts between months $t-1$ and t as $\Delta F_tEPS_{t+h} = F_tEPS_{t+h} - F_{t-1}EPS_{t+h}$. Similarly, the change in PTGs is defined as $\Delta PTG_t = PTG_t - PTG_{t-1}$. We drop negative sales forecasts and negative gross margin forecasts (less than 0.5% of our sample) and define the change in sales forecasts as $\Delta F_tSales_{t+h} = F_tSales_{t+h} - F_{t-1}Sales_{t+h}$ and the change in gross margin forecasts as $\Delta F_tGrossMargin_{t+h} = F_tGrossMargin_{t+h} - F_{t-1}GrossMargin_{t+h}$. In the regressions, we scale forecast changes by initial forecasts, that is, we use $\frac{\Delta F_tEPS_{i,t+h}}{abs(F_{t-1}EPS_{i,t+h})}$, $\frac{\Delta PTG_t}{PTG_{t-1}}$, $\frac{\Delta F_tSales_{t+h}}{F_{t-1}Sales_{t+h}}$ and $\frac{\Delta F_tGrossMargin_{t+h}}{F_{t-1}GrossMargin_{t+h}}$ as the dependent variables.[4] Since LTG forecasts are already in percentage terms, we directly use the change $\Delta LTG_t = LTG_t - LTG_{t-1}$ as the dependent variable.

In our regressions, we control for observed changes in firms' key fundamentals. We first forward-fill the annual accounting variables to the monthly level, time-stamped based on the publication date of the financial statement. Next, we construct the changes in firms' return on assets (ROA), capital expenditures, and net debt—$\Delta ROA_t = ROA_t - ROA_{t-1}$, $\Delta(\frac{Capx}{Asset})_t = (\frac{Capx}{Asset})_t - (\frac{Capx}{Asset})_{t-1}$, and $\Delta(\frac{NetDebt}{Asset})_t = (\frac{NetDebt}{Asset})_t - (\frac{NetDebt}{Asset})_{t-1}$, respectively. By construction, the controls in month t are nonzero only if a new financial statement is published in month t. We winsorize all ratios at 2.5% and 97.5% to remove the impact of outliers.

Our final sample spans from 2008 to 2019, and includes 81,749 ESG incidents for 9,737 firms in 49 countries or regions.[5] The sample includes 744,858 unique firm-month observations, of which 10.44% of firm-months have at least one incident (6.57% have exactly one incident and 3.87% have at least two incidents) and on average 0.23 ESG incidents happen in each month.[6] There are 2,976,889 EPS forecasts, 2,831,931 sales forecasts, 1,442,110 gross margin forecasts at the firm-month-horizon level, and 688,899 PTG forecasts

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

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

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

and 253,735 LTG forecasts at the firm-month level. In the full firm-month-measure-horizon panel sample, 7.57% of observations have exactly one ESG incident and 4.82% have at least two ESG incidents. Table II reports summary statistics for the main variables used in the analysis.

II. Analysts' Reactions to ESG Incidents

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

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

The dependent variable is the change in the consensus EPS forecasts between consecutive months $t-1$ and t, scaled by the absolute value of the consensus EPS forecast in month $t-1$. We also consider changes in LTG forecasts, analyst-implied returns based on price targets, which we calculate as the change in the consensus PTG between months $t-1$ and t scaled by the PTG in month $t-1$, as well as realized returns. The main independent variable in these tests is an indicator variable equal to one if RepRisk reports at least one ESG incident between months $t-6$ and t. We cumulate ESG incidents to give both the market and analysts enough time to react to them. In Internet Appendix Table IA.III, in which we explore the effect of past incidents on current reactions, we find that incidents affect analyst forecast changes for up to 12 months, while the market reacts more quickly to these incidents. Our results are robust to aggregating the ESG incidents over months $[t-3,t]$, $[t-9,t]$, or $[t-12,t]$ (see Internet Appendix Table IA.IV).[7]

We include firm fixed effects (σ_i in equation (1)) in these regressions, so that the tests exploit time variation only within firms. This allows us to address the possibility that some firm characteristics (e.g., size) are correlated with analyst forecast revisions as well as with the occurrence of ESG incidents (e.g., through media coverage intensity). We also include industry × country × month fixed effects ($\gamma_{Country\times Industry\times t}$ in equation (1)), which absorb any country-level analyst forecast characteristics, any industry-level analyst forecast characteristics, and any time variation in analyst forecast revisions (e.g., due to changes

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

Table II

Summary Statistics

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

	Obs.	Mean	*SD*	p1	p25	p50	p75	p99
$\Delta EPS/EPS$ (%)	2,976,889	−1.23	8.31	−32.69	−1.46	0.00	0.04	20.00
ΔLTG (%)	253,735	−0.12	1.82	−6.30	0.00	0.00	0.00	5.32
$\Delta PTG/PTG$ (%)	688,899	0.22	5.68	−16.67	−0.56	0.00	1.45	16.67
Return (%)	737,689	0.35	9.93	−24.07	−5.18	0.55	6.13	23.42
$\Delta Sales/Sales$ (%)	2,831,931	−0.17	2.27	−7.68	−0.43	0.00	0.19	6.44
$\Delta GrossMargin/GrossMargin$ (%)	1,442,110	−0.13	1.94	−7.04	−0.06	0.00	0.00	5.72
Market Cap. (Bil USD)	8,193,510	10.14	28.88	0.08	0.98	2.73	8.10	133.22
ΔROA(%)	7,334,872	−0.00	0.11	−0.59	0.00	0.00	0.00	0.44
$\Delta(CapEx/Asset)$(%)	7,933,001	−0.01	0.21	−1.06	0.00	0.00	0.00	0.89
$\Delta(NetDebt/Asset)$(%)	7,915,217	0.01	0.56	−2.35	0.00	0.00	0.00	2.75
Any incidents	8,193,564	0.12	0.33	0.00	0.00	0.00	0.00	1.00
Num. of incidents	8,193,564	0.27	1.20	0.00	0.00	0.00	0.00	5.00

in macroeconomic conditions), as well as the interaction of these effects. We double-cluster standard errors at the firm and month levels to account for possible dependence across firms and months.

Panel A of Table III shows that the effect of ESG incidents on earnings forecasts is negative over all horizons, statistically significant for most horizons, and approximately constant across horizons. For example, the monthly change in earnings forecasts for the one-quarter horizon (−0.142%) is roughly equal to that for the two- or three-year horizons (−0.148% and −0.157%, respectively). We conclude that following ESG incidents, there is an almost parallel shift in analysts' EPS forecasts. This is confirmed in column (8), in which the effect of ESG incidents on the forecasted LTG of EPS is economically and statistically insignificant. The last two columns of the table report the relative change in PTGs and stock returns following ESG incidents. The two effects are significantly negative and of similar magnitudes. Analysts' downward adjustments of price targets (column (9)) are of a similar magnitude as observed price movements following ESG incidents (column (10)).[8]

In Panel B of Table III, we refine the analysis by considering how the number of incidents affects EPS forecasts, PTGs, and returns. Intuition suggests that analysts' reactions should increase with the number of incidents. In line with this intuition, the reactions are both economically and statistically significantly more pronounced for firms that have had at least two incidents compared to firms for which RepRisk reports only one incident. For example, decreases in EPS forecasts vary from approximately −0.001% to −0.119% across all forecast horizons for firms with one incident in months $[t-6, t]$, while they vary between −0.113% and −0.277% for firms with at least two incidents during the same period. Again, firms with the strongest analyst reactions, that is, those with at least two negative ESG events as reported by RepRisk, observe changes in analyst EPS forecasts that are roughly constant across all horizons.

We further explore heterogeneous effects across incident types. Table IV reports analyst reactions to incidents in the E, S, and G categories separately. The impact of E incidents on forecast changes appears to be less significant than that of S and G incidents, and S incidents appear to have a stronger impact than G incidents. The insignificance of E incidents may be due to the fact that E incidents are less serious on average than those in the two

[8] Our results are robust to alternative specifications. For example, the results hold when replacing month × industry × country fixed effects with only month × industry, month × country, or simply month fixed effects. Similarly, dropping firm fixed effects and adding firm-level controls leads to similar conclusions. Our results are also robust to adding firm-level time-varying controls, which addresses the concern that some time-varying firm characteristics are correlated with analyst forecast revisions as well as with ESG incidents. Our analysis confirms that ROA change, size, and book-to-market predict changes in analyst forecasts, consistent with Das, Levine, and Sivaramakrishnan (1998) and Engelberg, McLean, and Pontiff (2020). Our analysis is also robust to controlling for changes in firm fundamentals, and to scaling the EPS revisions by book value per share in the previous year rather than by lagged EPS forecasts. Results of these robustness tests are presented in Internet Appendix Tables IA.V–IA.IX.

Table III

Reaction of Earnings Forecasts to ESG Incidents

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

Panel A: At Least One Incident

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t−6,t]	−0.142**	−0.124*	−0.074	−0.049	−0.130***	−0.148***	−0.157***	0.002	−0.168***	−0.177***
	(−2.09)	(−1.85)	(−1.14)	(−0.83)	(−3.08)	(−3.76)	(−4.18)	(0.17)	(−6.20)	(−5.08)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

(*Continued*)

Table III—*Continued*

Panel B: Splitting by the Number of Incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
1 incident in months [t−6,t]	−0.082	−0.068	−0.001	−0.020	−0.090**	−0.110***	−0.119***	0.012	−0.132***	−0.167***
	(−1.15)	(−0.96)	(−0.01)	(−0.33)	(−2.12)	(−2.74)	(−3.11)	(0.93)	(−4.88)	(−4.83)
>=2 incidents in months [t−6,t]	−0.277***	−0.248***	−0.238**	−0.113	−0.222***	−0.236***	−0.240***	−0.019	−0.250***	−0.198***
	(−3.03)	(−2.79)	(−2.59)	(−1.27)	(-3.75)	(-4.39)	(-4.59)	(-1.21)	(-6.52)	(-3.99)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

Table IV

Reaction of Earnings Forecasts to ESG Incidents—By E/S/G Category

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

Panel A: Environmental Incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 E incidents in months [t−6,t]	−0.121	−0.029	−0.195**	−0.138	−0.100*	−0.109*	−0.094*	0.015	−0.083**	−0.080*
	(−1.23)	(−0.32)	(−2.10)	(−1.51)	(−1.70)	(−1.92)	(−1.77)	(0.89)	(−2.46)	(−1.70)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

(*Continued*)

Table IV—*Continued*

Panel B: Social Incidents	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 S incidents in months [t−6,t]	−0.149**	−0.194***	−0.125*	−0.077	−0.175***	−0.189***	−0.180***	0.002	−0.169***	−0.142***
	(−2.15)	(−2.99)	(−1.92)	(−1.20)	(−4.23)	(−4.86)	(−4.77)	(0.14)	(−6.13)	(−4.08)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

Panel C: Governance Incidents	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 G incidents in months [t−6,t]	−0.162**	−0.051	0.020	0.012	−0.150***	−0.097**	−0.126***	−0.012	−0.143***	−0.142***
	(−2.06)	(−0.68)	(0.25)	(0.16)	(−3.13)	(−2.23)	(−3.22)	(−0.87)	(−4.24)	(−3.45)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

other categories. In Table V, we repeat this exercise separately for firms with one versus at least two incidents in each category. As in our previous tests, multiple incidents in any category have a larger impact on analyst reactions.

We also examine the effect of incidents by levels of novelty, severity, and reach provided by RepRisk. We define high- and low-novelty (respectively, severity and reach) incidents as incidents for which the level of novelty (severity and reach) is greater than or equal to two. Table VI shows the effects of high- and low-novelty (severity, and reach) incidents on analyst and market reactions. Incidents with high levels of novelty, severity, or reach have significantly negative effects on analyst forecasts at most horizons. In contrast, the coefficients on low-novelty and low-severity incidents are significant only at the one-year and three-year forecast horizons, respectively, and are not significant for low-reach incidents. These results confirm that the baseline effect is driven mainly by severe, novel, and high-reach incidents.

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

To compare the term structure effects of different events, we estimate their impact on earnings forecasts at different horizons as we do in Table III. We then normalize the estimated impact coefficients by their impact at the one-year horizon and represent them graphically in Figure 2.

As shown in Figure 2, the impact of ESG incidents on EPS forecasts persists over longer horizons more than that of other negative corporate news. On average, the impact of an ESG incident on earnings forecasts over the three-year horizon is about 21% higher (0.157/0.130 = 1.21, from Table III) than

[9] Note that the impact of ESG incidents on EPS forecasts documented in Table III is robust to controlling for other types of negative incidents in Capital IQ's Key Developments database. Internet Appendix Figure IA.1 reports the effect of ESG incidents on one-, two-, and three-year EPS forecasts and returns after controlling for the occurrence of other types of incidents (one type at a time). The effects of ESG incidents on EPS forecasts and returns are remarkably similar to those obtained in the baseline regression (Table III) economically and statistically. This suggests that Reprisk's ESG incidents are above and beyond the other types of incidents reported in the Capital IQ database. We also control for all the other incidents simultaneously. As shown in Internet Appendix Table IA.XI, the results remain robust and the magnitude is comparable to the baseline results without these controls.

Table V

Reaction of Earnings Forecasts to ESG Incidents—By E/S/G Category (Two or More Events)

This table reports results of regressions of changes in EPS consensus forecasts, PTG, and returns on ESG incidents. In columns (1) to (7), the dependent variables are the changes in the one-quarter, two-quarter, three-quarter, four-quarter, one-year, two-year, and three-year horizon EPS forecasts, defined as $\frac{F_tEPS_{t+h}-F_{t-1}EPS_{t+h}}{abs(F_{t-1}EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined by $(LTG_t - LTG_{t-1})$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t-PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the cumulative return over month t. In Panel A, the independent variables are two separate dummy variables indicating if one or two and more environmental incidents happen in months $[t-6, t]$. In Panel B, the main independent variables are two separate dummy variables indicating if one or two and more social incidents happen in months $[t-6, t]$. In Panel C, the independent variables are two separate dummy variables indicating if one or two and more governance incidents happen in months $[t-6, t]$. Standard errors are double-clustered at the firm and month level. t-Statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Environmental Incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
1 E incident in months [t−6,t]	−0.058	0.026	−0.171*	−0.074	−0.093	−0.077	−0.077	0.027	−0.053	−0.064
	(−0.57)	(0.28)	(−1.81)	(−0.81)	(−1.60)	(−1.35)	(−1.42)	(1.62)	(−1.55)	(−1.27)
>=2 E incidents in months [t−6,t]	−0.282*	−0.168	−0.255*	−0.300*	−0.120	−0.197**	−0.142*	−0.018	−0.168***	−0.125*
	(−1.92)	(−1.17)	(−1.82)	(−1.97)	(−1.25)	(−2.35)	(−1.70)	(−0.76)	(−3.19)	(−1.94)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

(*Continued*)

Table V—*Continued*

Panel B: Social Incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
1 S incident in months [t−6,t]	−0.096	−0.135*	−0.055	−0.015	−0.138***	−0.155***	−0.151***	0.015	−0.141***	−0.138***
	(−1.29)	(−1.92)	(−0.85)	(−0.22)	(−3.24)	(−3.70)	(−3.90)	(1.20)	(−5.04)	(−3.98)
>=2 S incidents in months [t−6,t]	−0.267***	−0.325***	−0.279***	−0.211**	−0.258***	−0.266***	−0.241***	−0.026*	−0.232***	−0.151***
	(−2.86)	(−3.64)	(−2.94)	(−2.40)	(−4.31)	(−4.94)	(−4.74)	(−1.69)	(−6.09)	(−3.07)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

Panel C: Governance incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
1 G incident in months [t−6,t]	−0.121	−0.004	0.060	0.041	−0.108**	−0.073	−0.127***	−0.003	−0.138***	−0.171***
	(−1.57)	(−0.05)	(0.73)	(0.51)	(−2.20)	(−1.65)	(−3.04)	(−0.21)	(−3.93)	(−4.13)
>=2 G incidents in months [t−6,t]	−0.258**	−0.163	−0.074	−0.056	−0.251***	−0.154**	−0.124**	−0.031*	−0.153***	−0.070
	(−2.02)	(−1.50)	(−0.66)	(−0.59)	(−3.42)	(−2.44)	(−2.26)	(−1.70)	(−3.24)	(−1.06)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

Table VI

Reaction of Earnings Forecasts to ESG Incidents, by Novelty, Severity, and Reach

This table reports results of regressions of changes in EPS consensus forecasts, PTG, and returns on ESG incidents of different levels of novelty, severity, and reach. In columns (1) to (7), the dependent variables are changes in the one-quarter, two-quarter, three-quarter, four-quarter, one-year, two-year, and three-year horizon EPS forecasts, defined as $\frac{F_t EPS_{t+h} - F_{t-1} EPS_{t+h}}{abs(F_{t-1} EPS_{t+h})} \times 100$, where h is the horizon of the forecasts. In column (8), the dependent variable is the change in the LTG forecast, defined as $(LTG_t - LTG_{t-1})$. In column (9), the dependent variable is the change in the PTGs, defined as $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} \times 100$. In column (10), the dependent variable is the return in month t. In Panel A, the independent variables are two dummy variables equal to one if at least one high- or low-novelty incident occurs in months $[t-6, t]$, respectively. In Panel B, the main independent variables are two dummy variables equal to one if at least one high- or low-severity incident occurs in months $[t-6, t]$, respectively. In Panel C, the independent variables are two dummy variables equal to one if at least one high- or low-reach incident occurs in months $[t-6, t]$, respectively. Low-novelty, low-severity, and low-reach incidents are RepRisk incidents with novelty, severity, and reach level, respectively, equal to one. High-novelty, high-severity, and high-reach incidents are RepRisk incidents with novelty, severity, and reach levels, respectively, equal to 2 or 3. Standard errors are double-clustered at the firm and month levels. t-Statistics are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: High- versus Low-Novelty Incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 low-novelty incidents in months [t−6,t]	−0.167*	−0.104	−0.012	−0.045	−0.121**	−0.079	−0.071	−0.000	−0.086**	−0.071
	(−1.74)	(−1.22)	(−0.14)	(−0.52)	(−2.10)	(−1.49)	(−1.49)	(−0.00)	(−2.53)	(−1.59)
>=1 high-novelty incidents in months [t−6,t]	−0.097	−0.098	−0.089	−0.043	−0.109**	−0.145***	−0.152***	−0.006	−0.164***	−0.152***
	(−1.49)	(−1.41)	(−1.34)	(−0.76)	(−2.61)	(−3.64)	(−3.84)	(−0.52)	(−6.10)	(−4.44)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

(*Continued*)

Table VI—*Continued*

Panel B: High- versus Low-Severity Incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 low-severity incidents in months [t−6,t]	−0.127**	−0.042	0.007	0.044	−0.025	−0.075*	−0.091***	−0.005	−0.117***	−0.110***
	(−2.01)	(−0.67)	(0.12)	(0.71)	(−0.60)	(−1.97)	(−2.63)	(−0.45)	(−4.49)	(−3.07)
>=1 high-severity incidents in months [t−6,t]	−0.150*	−0.173**	−0.180**	−0.207***	−0.195***	−0.163***	−0.134***	−0.013	−0.144***	−0.108**
	(−1.91)	(−2.24)	(−2.30)	(−2.99)	(−3.88)	(−3.66)	(−3.39)	(−1.05)	(−4.43)	(−2.61)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

Panel C: High- versus Low-Reach Incidents

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 low-reach incidents in months [t−6,t]	−0.005	−0.079	−0.062	−0.083	−0.025	−0.010	−0.037	0.017	−0.092***	−0.071*
	(−0.07)	(−1.20)	(−0.94)	(−1.32)	(−0.53)	(−0.23)	(−0.87)	(1.58)	(−3.05)	(−1.74)
>=1 high-reach incidents in months [t−6,t]	−0.208***	−0.108	−0.078	−0.066	−0.151***	−0.184***	−0.159***	−0.017	−0.159***	−0.153***
	(−2.93)	(−1.59)	(−1.21)	(−0.93)	(−3.63)	(−4.69)	(−4.56)	(−1.31)	(−5.69)	(−4.56)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

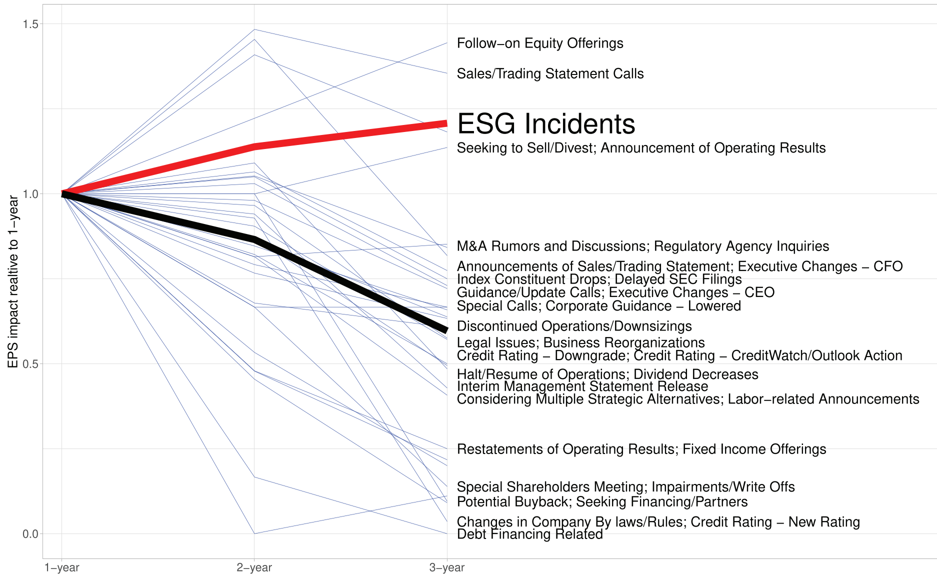


Figure 2. Term structure of the impact of incidents on earnings forecasts. This figure reports the term structure of different types of *negative* corporate events. For each event type u and horizon h, we estimate $\frac{\Delta F_t EPS_{i,t+h}}{abs(F_{t-1}EPS_{i,t+h})} = \alpha + \beta_h\, \mathbb{1}\{type\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

the impact of an ESG incident on one-year earnings forecasts. By contrast, the impact of other types of events diminishes over time. For example, for credit rating downgrades, the impact on three-year earnings forecasts is 42% lower ($0.84/1.46 = 0.58$; see Internet Appendix Table IA.X) than the impact on one-year earnings forecasts. A similar term structure appears when we use a regression setting. Specifically, we run the regression

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

Table VII reports the estimation results for the above equation. Columns (1) to (3) report the impacts of negative KD and ESG incidents on earnings forecasts. The impact of an average negative KD event decreases from 0.48% for one-year forecasts to 0.39% for two-year forecasts and 0.29% for three-year forecasts. These differences are significant, as shown in the pooled regressions in columns (4) and (5). In contrast, the difference in the impact of ESG incidents across horizons is not significant (columns (4) and (5)). The F-tests in columns (4) and (5) show that there is a significant difference between the term structure of ESG incidents and that of average negative KD incidents. We conclude that ESG incidents have a longer lived impact on earnings forecasts than other types of negative incidents.

III. Economic Mechanism: Sales versus Costs

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

To understand through which of these two channels (sales versus costs) analysts anticipate ESG incidents to affect future earnings, we estimate two sets of regression equations similar to equation (1) but in which we replace changes in earnings forecasts with changes in sales forecasts ($\frac{\Delta F_t Sales_{i,t+h}}{F_{t-1} Sales_{i,t+h}}$) and 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 VIII reports results of these regressions. The analysis suggests that the anticipated decrease in earnings documented earlier is driven by a decrease in both expected sales and expected profit margins. In terms of magnitudes, the reduction in EPS appears to be driven primarily by a reduction in sales. The coefficients on the ESG incident dummy variable are consistently negative and statistically significant over most horizons (see columns (1) to (7) of Panel A), where we use changes in expected sales as the dependent variable. Columns (1) to (7) of Panel B suggest that this effect is more pronounced for firms with multiple incidents, similar to the effects on earnings forecasts.[10] In contrast, the coefficients on the ESG incident dummy variable in the gross margin regressions (in columns (8) to (14) of Panel A) are significant only at the one-quarter, one-year, and two-year

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

Table VII

Impact of ESG Incidents and Other Incidents on EPS Forecasts

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

	(1) One Year	(2) Two Years	(3) Three Years	(4) One&Two Years	(5) One&Three Years
>=1 ESG Incidents in months [t−6,t]	−0.126***	−0.145***	−0.156***	−0.126***	−0.126***
	(−3.03)	(−3.75)	(−4.23)	(−3.04)	(−3.04)
>= 1 KD Negative Incidents in months [t−6,t]	−0.482***	−0.387***	−0.288***	−0.482***	−0.482***
	(−11.26)	(−10.51)	(−8.13)	(−11.35)	(−11.36)
>=1 ESG Incidents in months [t−6,t] × 2-year				−0.019	
				(−0.59)	
>= 1 KD Negative Incidents in months [t−6,t] × 2-year				0.095***	
				(3.39)	
>=1 ESG Incidents in months [t−6,t] × 3-year					−0.030
					(−0.74)
>= 1 KD Negative Incidents in months [t−6,t] × 3-year					0.194***
					(5.21)
$\beta_{ESG\times h-year}-\beta_{KD\times h-year}$				−0.115	−0.224
F-stat				7.049	16.661
P value				0.009	0.000
Month × Industry × Country FE	YES	YES	YES	NO	NO
Firm FE	YES	YES	YES	NO	NO
Month × Industry × Country × Horizon FE	NO	NO	NO	YES	YES
Firm × Horizon FE	NO	NO	NO	YES	YES
Adj. R^2	0.084	0.100	0.079	0.092	0.082
Obs.	661,466	649,616	500,617	1,311,082	1,162,083

Table VIII

Reaction of Sales and Gross Margin Forecasts to ESG Incidents

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

Panel A: At Least One Incident

	Sales							GrossMargin						
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) Q1	(9) Q2	(10) Q3	(11) Q4	(12) One Year	(13) Two Years	(14) Three Years
>=1 incidents in months [t−6,t]	−0.018	−0.035**	−0.037**	−0.019	−0.036***	−0.055***	−0.061***	−0.033*	−0.025	0.008	0.020	−0.027**	−0.028**	−0.013
	(−1.17)	(−2.05)	(−2.28)	(−1.22)	(−3.81)	(−4.75)	(−5.04)	(−1.78)	(−1.35)	(0.41)	(1.26)	(−2.53)	(−2.26)	(−1.04)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.096	0.098	0.096	0.098	0.084	0.097	0.083	0.055	0.046	0.044	0.051	0.055	0.049	0.044
Obs.	287,848	257,668	229,055	132,583	635,184	622,496	480,707	133,105	121,208	106,544	62,080	348,421	337,610	222,117

(*Continued*)

Table VIII—*Continued*

Panel B: Splitting by the Number of Incidents

	Sales							GrossMargin						
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) Q1	(9) Q2	(10) Q3	(11) Q4	(12) One Year	(13) Two Years	(14) Three Years
1 incident in months [t−6,t]	−0.006	−0.014	−0.010	−0.013	−0.028***	−0.038***	−0.043***	−0.038**	−0.019	0.018	0.021	−0.030**	−0.026**	−0.000
	(−0.36)	(−0.78)	(−0.63)	(−0.75)	(−2.90)	(−3.23)	(−3.30)	(−2.11)	(−1.03)	(0.88)	(1.29)	(−2.35)	(−1.98)	(−0.02)
>=2 incidents in months [t−6,t]	−0.045**	−0.081***	−0.096***	−0.033	−0.054***	−0.095***	−0.099***	−0.021	−0.039	−0.015	0.019	−0.021	−0.033**	−0.041**
	(−2.04)	(−3.74)	(−4.29)	(−1.60)	(−3.93)	(−5.74)	(−5.88)	(−0.78)	(−1.57)	(−0.61)	(0.80)	(−1.56)	(−2.14)	(−2.38)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.096	0.098	0.096	0.098	0.084	0.097	0.083	0.055	0.046	0.044	0.051	0.055	0.049	0.044
Obs.	287,848	257,668	229,055	132,583	635,184	622,496	480,707	133,105	121,208	106,544	62,080	348,421	337,610	222,117

horizons. In addition, in terms of magnitudes, the coefficients in the gross margin regressions are smaller than those in the sales regressions. Based on the estimation using annual forecasts, following an ESG incident, expected sales decrease by around 0.051% ($\frac{0.036+0.055+0.061}{3}$), and expected gross margins decrease by 0.023%($\frac{0.027+0.028+0.013}{3}$). Thus, the decrease in expected sales following an ESG incident is around twice as large as the decrease in expected gross margins. The difference in magnitude also shows up when considering multiple incidents in Panel B. This divergence between sales and margin forecasts is not caused by a difference in the numbers of observations, as confirmed in Internet Appendix Table IA.XIII using a balanced sample.

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

Overall, these results suggest that the impact of ESG news on earnings forecasts is likely to come primarily from a customer channel, that is, analysts expect customers to avoid buying from firms that fail to comply with ESG standards.[11] This finding is consistent with Duan, Li, and Michaely (2024) and Houston et al. (2024), who use retail store data to show that consumer demand decreases following negative ESG incidents. Analysts are able to incorporate the lower future consumer demand by adjusting sales forecasts after the occurrence of negative ESG incidents.

IV. Impact on Firm Value: Cash Flow versus Discount Rates

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

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

A. A First Intuitive Pass Using Gordon's Formula

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

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

where PV_{it} is the equity value of firm i at time t, b_i is the payout ratio (assumed to be constant over time within firms), $F_t EPS_{i,t+1}$ is the time t forecast of the next 12 months' earnings, r_{it} is the discount rate of firm i at time t, and g_{it} is the expected growth rate of earnings of firm i at time t. The theoretical firm-level return induced by an ESG information shock is

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

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

B. A Discounted Dividends Approach

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

$$\begin{aligned}\frac{PV_{it}(r_{it})}{b_i} = &\frac{F_t EPS_{i,t+1}}{(1+r_{it})^{\theta_{it}}} + \frac{F_t EPS_{i,t+2}}{(1+r_{it})^{\theta_{it}+1}} + \frac{F_t EPS_{i,t+3}}{(1+r_{it})^{\theta_{it}+2}} \\ &+ \frac{1}{(1+r_{it})^{\theta_{it}+2}} \frac{(1+g_t) F_t EPS_{i,t+3}}{r_{it} - g_t},\end{aligned} \tag{4}$$

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

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

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

To better account for the underreaction of analysts and the potential difference in the speed of reaction between analysts and the market, we conduct an event study for the discount rate analysis in this section. Specifically, we define ESG incidents in a month as an "event" and investigate how analyst forecasts, returns, and implied discount rates change following an event, using the regression

$$y_{t,t+s} = \alpha + \beta\, \mathbb{1}\{ESG\ incidents\ in\ month\ t\} + \gamma_{Country\times Industry\times t} + Controls + \epsilon_{i,t}, \tag{6}$$

where $s = 0, 1, 2, \ldots, 6$ indicate the window (in months) following an incident, with $s = 0$ the month in which the incident happens. To capture the value change from updated EPS forecasts, we calculate the new firm value $\widehat{PV_{i,t+s}}$ using the formula above with updated analyst forecasts in month $t + s$ and the same discount rate, growth rate, and payout ratio as in month $t - 1$. We then calculate the percentage change in value between months $t - 1$ and $t + s$, $\frac{\widehat{PV_{i,t+s}} - PV_{i,t-1}}{PV_{i,t-1}}$, which is the predicted stock return if ESG shocks affect expected profitability but not the discount rate. The dependent variable, $y_{t,t+s}$, is the value change implied by the change in EPS forecasts (in column (1)), the return (in column (3)), or the change of implied discount rate (r, which is the solution of equation (5)) in each month (in column (5)) between months t and $t + s$. The main independent variable of interest is a dummy variable indicating whether any ESG incident happened in month t. Control variables include firm size and book-to-market ratio quintiles of firms.

The results are reported in Table IX. Each column shows the estimated β from the regression above and corresponding t-statistics. In the contemporaneous month, the market reaction is -0.24% (column (3)), while the implied value change from EPS forecast reaction is only -0.08% (column (1)). Such reactions jointly imply a contemporaneous change in discount rate $\frac{\Delta r}{r}$ of 0.05% (column (5)), which is also statistically significant (t-statistic = 2.08). This is due to analysts reacting slower than the market. Over wider postevent windows, the implied value change from EPS forecast reaction becomes larger. After three months ($[t, t + 3]$), analysts' reaction is -0.41% (column (1)) and the market return is -0.30% (column (3)). As a result, the inferred discount rate change is equal to -0.01% (column (5)) and statistically insignificant

Table IX

Event Study: Analysts and Market Reaction after an ESG Incident

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

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

(t-statistic $= -0.11$). Implied changes in discount rates keep decreasing but remain insignificant as we expand the window to $[t, t+6]$. The conclusion is that the change in EPS forecast can account for all of the changes in market return, even if the discount rate does not change. Regression analysis similar to equation (1) leads to a similar conclusion, as shown in Internet Appendix Table IA.XVI.

To summarize, cash flow effects are large enough to explain observed changes in firm valuations following ESG incidents. The change in implied discount rate is not statistically significant and is very small in magnitude.[12] One caveat is that our test of discount rate changes may lack statistical power and therefore we cannot fully rule out a change in discount rates.

V. Heterogeneity

In this section, we ask whether the effects of ESG incidents on forecasts and returns vary across countries, industries, and firms. The objective of this

[12] A limitation of this estimation is that we only run the internal rate of return (IRR) analysis for the U.S. sample. Although later analyses in Section V.A suggest that the effects do not differ between different areas, ESG incidents could potentially affect discount rates differently outside the United States.

analysis is to better understand what drives the sensitivity of analysts to ESG-related events (e.g., local industry composition or local sensitivity to environmental or social issues).

A. Variation across Geographic Regions

We first analyze the heterogeneity across countries, splitting the sample by geographic region. It is possible that the downward adjustment in sales and earnings forecasts varies across regions, for instance, because of geographic differences in consumer preferences. To test this hypothesis, we use firms located in North America (the United States and Canada) as the base category and further interact the ESG incident variables with the dummies $EU15$, $Asia$, and $Others$, where $EU15$ indicates the 15 most developed countries in Europe as defined by the United Nations[13] and $Others$ mostly includes firms in South America, Australia, and Africa. We focus on annual forecast data, as quarterly forecasts are predominantly available for U.S. firms.

Panel A of Table X reports the effects of ESG incidents on EPS, PTGs, and returns across regions. At short horizons (one to two years), there is no significant difference between forecasts for North American firms and firms located in other regions, while some differences across regions appear in longer-horizon forecasts. The interaction of the ESG incident variables and dummies indicateing firms from the $Others$ geographic regions is weakly significant and positive, implying that the three-year earnings forecasts for firms in the $Others$ region react less to ESG incidents than in other geographic areas. There is not much difference in terms of PTG reactions. In contrast, the average reaction in terms of cumulative returns in developed Europe is stronger than that in North America (see column (6)). Panel B of Table X reports the heterogeneous effects on the sales forecasts of firms by geographic region. We find no significant evidence of a difference across regions in sales forecasts, which is broadly consistent with the results for the earnings forecasts. From the evidence above, we conclude that downward adjustments in earnings forecasts are largely a global phenomenon with only slight geographic differences. For short-horizon forecasts, analysts react similarly for North American firms and firms in other regions, but there is some weak evidence that analysts react less firms in $Others$ geographic regions than for North American firms over longer forecast horizons.

B. Variation across Industries

We next ask whether the link between ESG-related news and analyst forecast revisions is stronger in some industries. Industries vary significantly in

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

Table X

Variation across Regions

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

Panel A: EPS/PTG Forecasts and Returns

	(1) One Year	(2) Two Years	(3) Three Years	(4) LTG	(5) PTG	(6) Return
>=1 incidents in months [t−6,t]	−0.082	−0.126**	−0.233***	−0.009	−0.180***	−0.112*
	(−1.21)	(−2.02)	(−3.73)	(−0.66)	(−3.95)	(−1.82)
>=1 incidents in months [t−6,t] × EU15	−0.080	−0.077	0.101	0.038	−0.042	−0.185*
	(−0.67)	(−0.77)	(1.15)	(1.33)	(−0.54)	(−1.85)
>=1 incidents in months [t−6,t] × Asia	−0.100	−0.042	0.099	0.016	0.011	−0.091
	(−1.06)	(−0.55)	(1.22)	(0.54)	(0.18)	(−1.16)
>=1 incidents in months [t−6,t] × Others	−0.003	0.031	0.173*	0.019	0.103	−0.050
	(−0.03)	(0.26)	(1.80)	(0.40)	(1.25)	(−0.49)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Adj. R^2	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	661,466	649,616	500,617	226,021	645,591	638,384

(*Continued*)

Table X—*Continued*

Panel B: Sales Forecasts	(1) One Year	(2) Two Years	(3) Three Years
>=1 incidents in months [t−6,t]	−0.027*	−0.056***	−0.073***
	(−1.78)	(−3.17)	(−3.68)
>=1 incidents in months [t−6,t] × EU15	0.015	−0.008	0.003
	(0.59)	(−0.28)	(0.09)
>=1 incidents in months [t−6,t] × Asia	−0.022	0.011	0.045
	(−1.10)	(0.46)	(1.64)
>=1 incidents in months [t−6,t] × Others	−0.022	−0.010	−0.029
	(−0.73)	(−0.29)	(−0.69)
Month × Industry × Country FE	YES	YES	YES
Firm FE	YES	YES	YES
Adj. R^2	0.084	0.097	0.083
Obs.	635,184	622,496	480,707

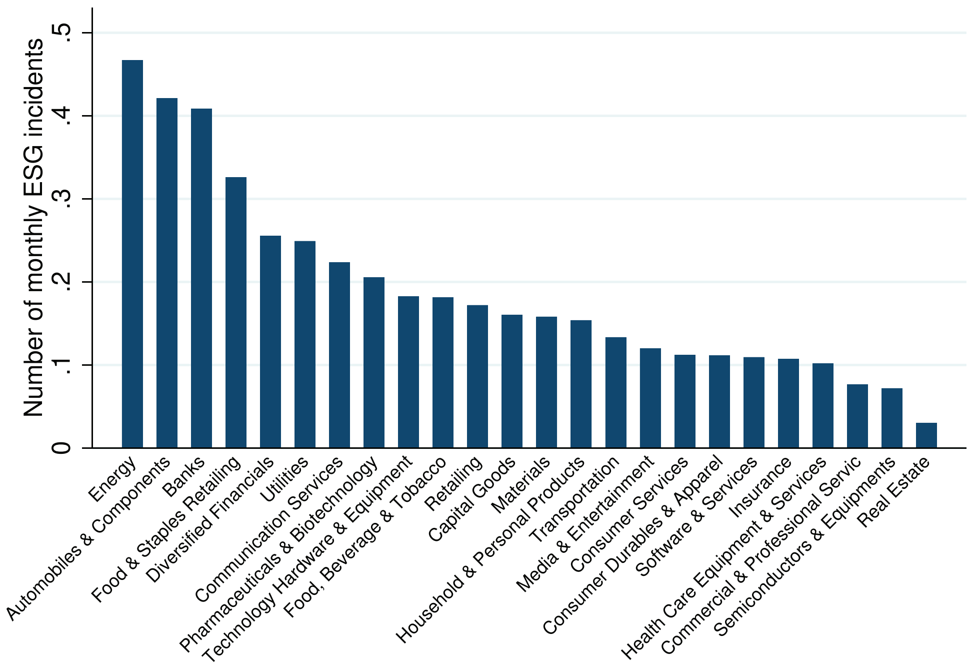


Figure 3. Number of incidents by industry. This figure shows the monthly average number of incidents by industry. Industries are defined according to GICS2 classification. (Color figure can be viewed at wileyonlinelibrary.com)

their exposure to ESG events. The average number of incidents per industry appears in Figure 3, which shows, for example, that firms in the energy sector are more likely to have ESG incidents in the average month than firms in the real estate sector.

Additionally, our previous results show that ESG performance influences future earnings mostly through reduced customer demand. Customers at different locations in the supply chain may have not only different access to information regarding the ESG practices of the firms from which they buy, but also different sensitivities to the ESG practices of those firms. Our hypothesis is that end customers are both less informed about and more sensitive to the ESG practices of the firms they buy from, so the effect of salient news items such as those reported by RepRisk should be more pronounced in B2C industries than in business-to-business (B2B) industries. To examine this possibility, we first calculate analysts' sensitivity to ESG news at the industry level using the same setting as in Table III above. We consider the average sensitivity of one-, two-, and three-year earnings forecasts to RepRisk news across all firms in each industry (as defined by GICS2 codes) as our industry measure of ESG sensitivity.

Figure 4 plots analysts' sensitivity to incidents in each industry, from the greatest sensitivity (i.e., the industry with the most negative coefficients in

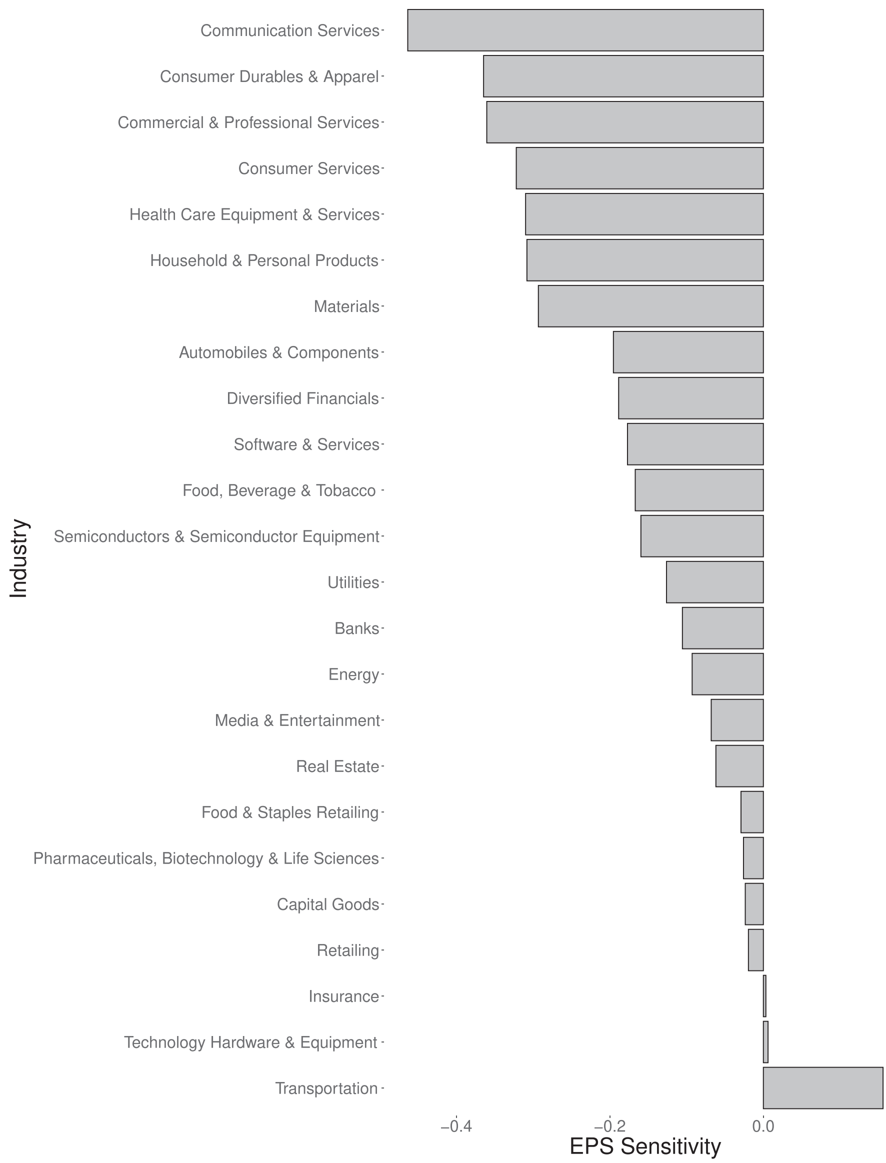


Figure 4. EPS sensitivity by industry. This figure shows the sensitivity of EPS forecasts by industry. The y-axis corresponds to industries (GICS2), and the x-axis to the sensitivity of the EPS forecasts to ESG incidents, measured by $\beta_{j,h}$ from the regression equation $\frac{F_t EPS_{i,t+h} - F_{t-1} EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta_j^h \, \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$. The sensitivity of industry j is measured as the average sensitivity across the one- to three-year horizon forecasts, that is, $(\beta_j^1 + \beta_j^2 + \beta_j^3)/3$.

the regressions of analysts' forecast changes on ESG-related events) to the lowest sensitivity. As expected, analysts seem to exhibit higher sensitivity to ESG-related news when firms belong to industries selling to end customers. For example, the four industries in which analysts are most sensitive to negative ESG incidents are "Communication Services," "Consumer Durables & Apparel," "Commercial & professional services," and "Consumer services." In line with our previous findings that PTG revisions by analysts are commensurate with their earnings forecast revisions, the ranking of industries using the sensitivity of PTG revisions to ESG news presented in Figure 5 is similar to the ranking presented in Figure 4.

To confirm this result in a more formal setting, we proxy for the extent to which firms from specific industries sell to end customers using data on advertising expenses, following Servaes and Tamayo (2013). Figure 6 plots the advertising intensity of various industries (measured as $\frac{Advertisement\ Expense}{Revenue}$) against the industry-level sensitivity of analyst forecasts to ESG news. Panel A of the figure illustrates the sensitivity of earnings forecasts to ESG-related news, while Panel B illustrates the sensitivity of PTGs. Both panels show a downward-sloping relation, meaning that industries with larger advertising expenses also tend to exhibit greater sensitivity to ESG news in their analyst forecasts (i.e., they have more negative coefficients in Figures 4 and 5). In Table XI, we split the industries into two groups, B2C and B2B, according to whether the firm belongs to an industry that is above or below the median of all industries in terms of its advertising expenditure. We then repeat the baseline analysis of equation (1), adding to the regression the interaction between a dummy measuring high advertisement intensity and the indicator variable equal to one for firms experiencing ESG incidents. Although we do not find a statistically significant interaction coefficient between ESG incidents and the dummy identifying B2C industries according to advertisement expenses, the coefficient is negative and its magnitude is economically meaningful over the one- and two-year horizons (Panel A), which implies that the negative impact in B2C industries is almost twice as large as in B2C industries. Panel B of Table XI also suggests that sales forecast revisions after ESG incidents are stronger for firms in B2C industries over one- and two-year horizons.

C. Large versus Small Firms

We also analyze whether there is heterogeneity by firm size, which we measure using market capitalization. We split the sample into small and large firms. The incidence of RepRisk ESG news items is highly correlated with firm size. Figure 7 shows the number of incidents by size deciles relative to the smallest decile after taking out country $\times$ industry $\times$ month fixed effects. Firms in the 10th decile have on average 1.2 more incidents per month than firms in the first decile. Therefore, ESG news could possibly be too rare for any effect on small firms to be detectable. On the other hand, investors closely monitor the ESG performance of large firms and could anticipate ESG-related events before they are known to the wider public. Accordingly, in Table XII,

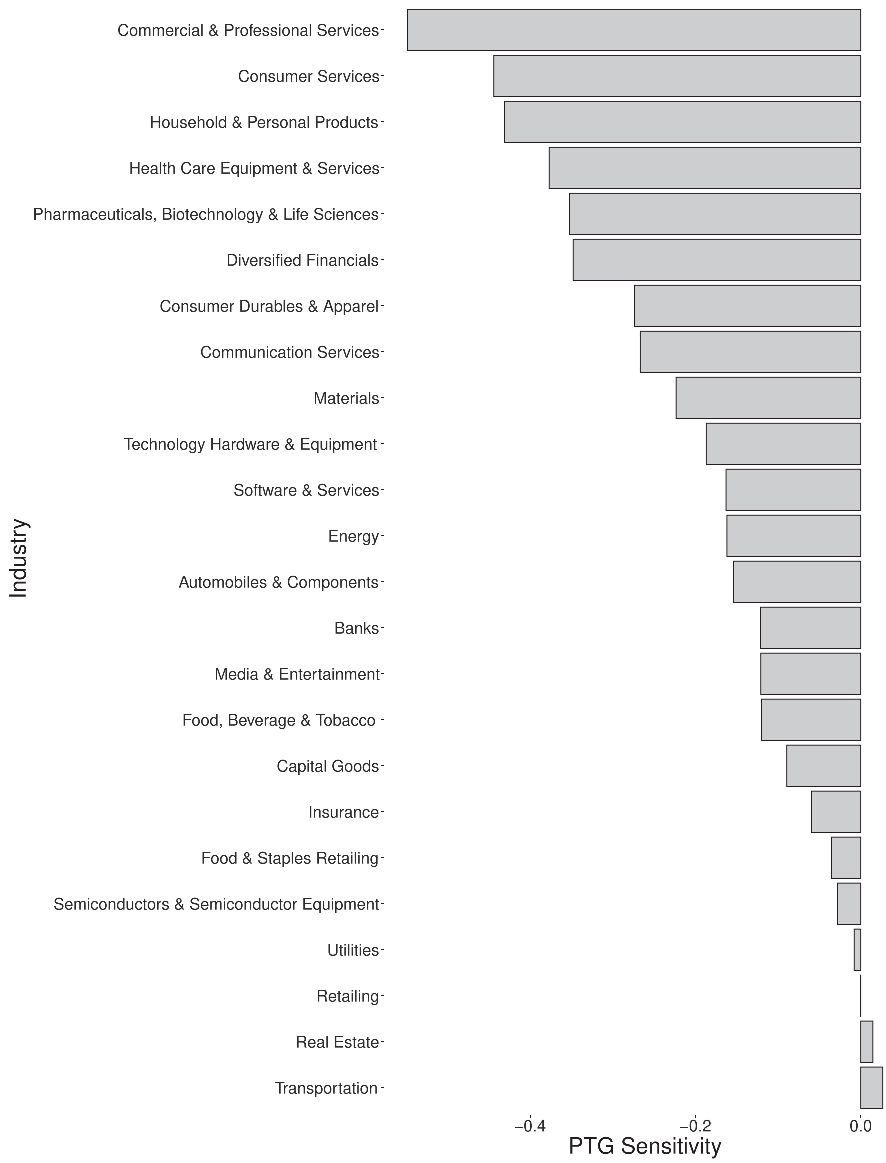
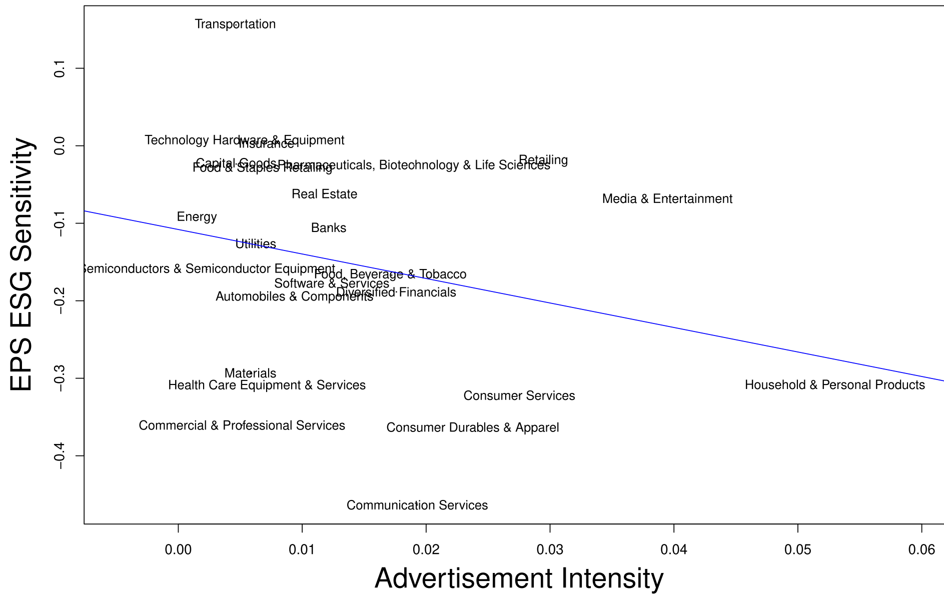


Figure 5. PTG sensitivity by industry. This figure shows the sensitivity of PTGs by industry. The y-axis corresponds to industries (GICS2), and the x-axis to the sensitivity of PTG forecasts to ESG incidents, measured by β_j from the regression equation $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} = \alpha + \beta_j \, \mathbb{1}\{ESG\ incidents\ in\ [t-6,t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$. The sensitivity of industry j is measured by β_j.

Panel A. EPS sensitivity



Panel B. PTG sensitivity

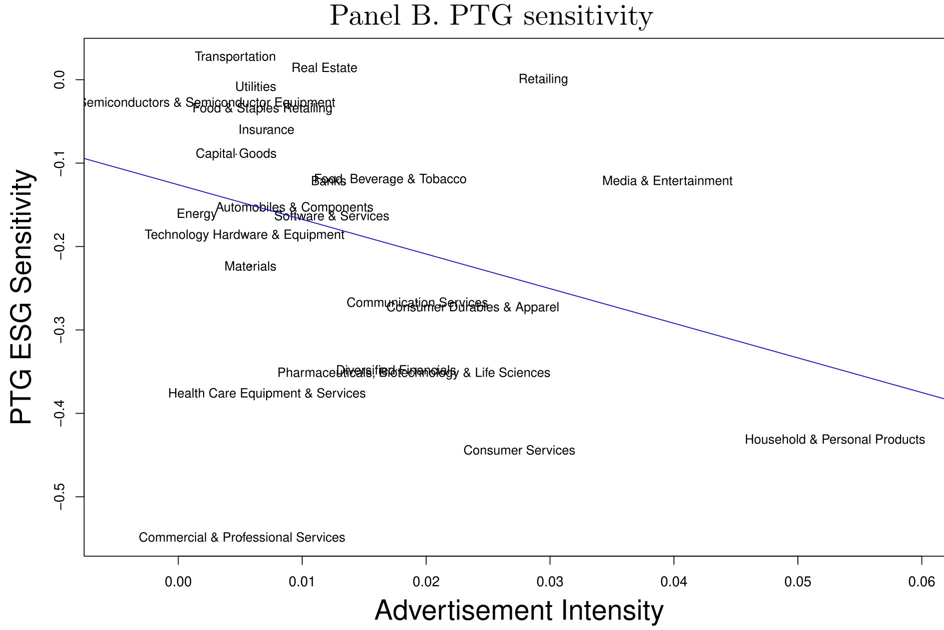


Figure 6. EPS/PTG sensitivity and advertising intensity. This figure depicts the relationship between ESG sensitivity and advertising intensity at the industry level. On the x-axis is advertising intensity, defined as $Advertising\,expenditure/Sales$. We take the median in an industry as the industry-level advertising intensity. The y-axis corresponds to the ESG

we split the sample of firms by firm size, with large firms being defined at the monthly level as those with above-median market capitalization in the given month. We then repeat the analysis of Table III for the two groups of firms. The results show that the effect of ESG events on analyst forecasts is stronger for small firms. The coefficient on the interaction between ESG events and the dummy variable equal to one for large firms compensates a large part of the coefficient on the event variable alone. In Panel B of Table XII, we repeat this analysis for sales forecasts. Analysts' downward revaluations of future sales that we document above seem to be slightly stronger for smaller firms. Overall, these results suggest that the information content of RepRisk events appears to be more relevant for smaller firms.

VI. Are Analysts Correct in Reacting to Negative ESG News?

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

$$\frac{Y_{i,t+h} - Y_{i,t-1}}{Y_{i,t-1}} = \alpha + \beta\, \mathbb{1}\{ESG\ incidents\ between\ year\ t-1\ and\ t\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}\ , \tag{7}$$

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

The results are presented in Table XIII. Panel A shows that, on average, having ESG incidents reported in a year decreases firms' realized net income by 8.8% to 11.8% (columns (1) to (3)), and decreases firms' realized sales by 1.2%

sensitivity measures. In Panel A, the y-axis plots the sensitivity of EPS forecasts to ESG incidents, measured by the average of β_j s from the regression $\frac{F_t EPS_{i,t+h} - F_{t-1} EPS_{i,t+h}}{abs(F_{t-1} EPS_{i,t+h})} = \alpha + \beta_j^h\, \mathbb{1}\{ESG\ incidents\ in\ [t-6, t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$ for each forecast horizon $h = 1, 2, 3$ years, that is, the sensitivity of industry j is measured by $(\beta_j^1 + \beta_j^2 + \beta_j^3)/3$. In Panel B, the y-axis plots the sensitivity of PTG forecasts to ESG incidents, measured by β_j from the regression equation $\frac{PTG_t - PTG_{t-1}}{PTG_{t-1}} = \alpha + \beta_j\, \mathbb{1}\{ESG\ incidents\ in\ [t-6, t]\} \times \mathbb{1}\{Industry = j\} + \gamma_{Country \times Industry \times t} + \sigma_i + \epsilon_{i,t}$. The sensitivity of industry j is measured by β_j. The blue lines in the two graphs are the corresponding linear fits. (Color figure can be viewed at wileyonlinelibrary.com)

Table XI

Interaction with Advertising Intensity

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

Panel A: EPS/PTG Forecasts and Returns

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t−6,t]	−0.087	−0.052	−0.022	−0.086	−0.091	−0.119**	−0.172***	−0.005	−0.144***	−0.162***
	(−0.95)	(−0.57)	(−0.26)	(−1.10)	(−1.58)	(−2.29)	(−3.54)	(−0.33)	(−4.37)	(−3.68)
>=1 incidents in months [t−6,t] × High Ad Intensity	−0.142	−0.180	−0.131	0.092	−0.100	−0.076	0.037	0.017	−0.062	−0.038
	(−1.09)	(−1.41)	(−1.21)	(0.88)	(−1.32)	(−1.13)	(0.63)	(0.74)	(−1.34)	(−0.56)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.093	0.084	0.100	0.079	0.072	0.173	0.373
Obs.	295,232	272,346	249,829	150,188	661,466	649,616	500,617	226,021	645,591	638,384

(*Continued*)

Table XI—*Continued*

Panel B: Sales Forecasts	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years
>=1 incidents in months [t−6,t]	−0.008	−0.016	−0.024	0.006	−0.024**	−0.042***	−0.047***
	(−0.41)	(−0.67)	(−1.03)	(0.27)	(−2.01)	(−2.93)	(−3.06)
>=1 incidents in months [t−6,t] × High Ad Intensity	−0.025	−0.047	−0.031	−0.060*	−0.031*	−0.034*	−0.037
	(−0.84)	(−1.51)	(−0.98)	(−1.94)	(−1.85)	(−1.69)	(−1.62)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.096	0.098	0.096	0.098	0.084	0.097	0.083
Obs.	287,848	257,668	229,055	132,583	635,184	622,496	480,707

Table XII

Interaction with Firm Size

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

Panel A: EPS/PTG Forecasts and Returns

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG	(9) PTG	(10) Ret.
>=1 incidents in months [t−6,t]	−0.193	−0.177	−0.197	−0.184*	−0.222***	−0.248***	−0.238***	−0.011	−0.205***	−0.216***
	(−1.65)	(−1.57)	(−1.65)	(−1.69)	(−3.36)	(−4.00)	(−3.63)	(−0.42)	(−5.10)	(−3.84)
>=1 incidents in months [t−6,t] × LargeFirm	0.082	0.086	0.197	0.214*	0.168**	0.180***	0.134*	0.017	0.068	0.066
	(0.59)	(0.68)	(1.46)	(1.74)	(2.36)	(2.77)	(1.90)	(0.61)	(1.52)	(0.90)
LargeFirm	0.670***	0.701***	0.629***	0.575***	0.642***	0.663***	0.616***	0.034	0.549***	−1.422***
	(5.39)	(5.31)	(4.72)	(4.55)	(8.57)	(8.83)	(8.63)	(1.54)	(9.50)	(−12.17)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.090	0.091	0.084	0.094	0.084	0.100	0.079	0.072	0.174	0.374
Obs.	295,231	272,345	249,829	150,188	661,461	649,610	500,615	226,021	645,589	638,383

(*Continued*)

Table XII—*Continued*

Panel B: Sales Forecasts

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years
>=1 incidents in months [t−6,t]	−0.020	−0.030	−0.044*	−0.046*	−0.041***	−0.070***	−0.056***
	(−0.87)	(−1.25)	(−1.75)	(−1.82)	(−3.20)	(−3.94)	(−2.94)
>=1 incidents in months [t−6,t] × LargeFirm	0.004	−0.008	0.011	0.042	0.010	0.027	−0.007
	(0.13)	(−0.27)	(0.36)	(1.46)	(0.61)	(1.31)	(−0.31)
LargeFirm	0.100***	0.118***	0.136***	0.053*	0.085***	0.141***	0.166***
	(3.64)	(4.18)	(4.72)	(1.85)	(5.30)	(6.94)	(7.54)
Month × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.096	0.099	0.096	0.098	0.084	0.097	0.083
Obs.	287,847	257,667	229,055	132,583	635,159	622,474	480,705

Table XIII

Impact of ESG Incidents on Realized Earnings, Sales, and Gross Margin

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

	Earnings			Sales			GrossMargin		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$
>=1 incidents year [t−1,t]	−0.088***	−0.118***	−0.091***	−0.012***	−0.026***	−0.042***	−0.003	−0.005	−0.002
	(−4.79)	(−4.79)	(−3.17)	(−5.43)	(−6.66)	(−8.06)	(−1.41)	(−1.37)	(−0.38)
Year × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.063	0.101	0.124	0.263	0.336	0.394	0.036	0.087	0.139
Obs.	83,420	79,549	73,309	85,293	81,247	75,107	73,582	70,077	64,519

(*Continued*)

Table XIII—*Continued*

Panel B: Splitting by the Number of Incidents

	Earnings			Sales			GrossMargin		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$	$t-1$ to t	$t-1$ to $t+1$	$t-1$ to $t+2$
Lower number of incidents year [t−1,t]	−0.071***	−0.086***	−0.069**	−0.011***	−0.023***	−0.038***	−0.003	−0.002	−0.000
	(−3.65)	(−3.34)	(−2.33)	(−4.60)	(−5.72)	(−7.27)	(−1.30)	(−0.60)	(−0.05)
Higher number of incidents year [t−1,t]	−0.145***	−0.233***	−0.179***	−0.017***	−0.037***	−0.057***	−0.004	−0.014**	−0.007
	(−5.20)	(−6.07)	(−3.80)	(−5.06)	(−6.09)	(−6.63)	(−1.01)	(−2.51)	(−1.02)
Year × Industry × Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.063	0.101	0.124	0.263	0.336	0.394	0.036	0.087	0.139
Obs.	83,420	79,549	73,309	85,293	81,247	75,107	73,582	70,077	64,519

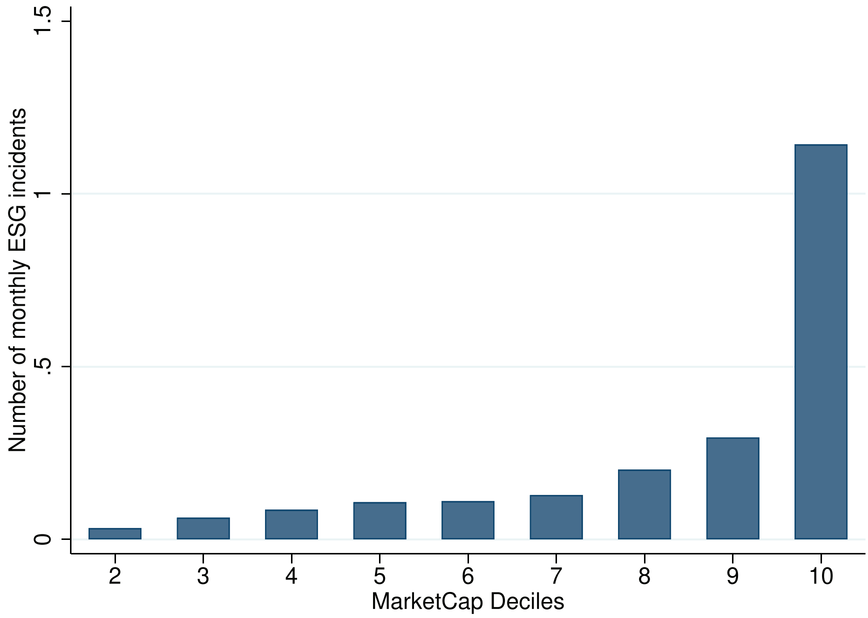


Figure 7. Number of incidents by firm size. This figure depicts the number of incidents by firm size deciles. The y-axis corresponds to the coefficients from the regression equation $num\_incidents_{i,t} = a + \sum_{j=2}^{10} b_j \mathbf{1}\{i \in SizeDecile_j\} + Industry \times month \times country\ FE + \epsilon_{i,t}$, where $num\_incidents_{i,t}$ is the number of RepRisk ESG incidents for firm i in month t. The x-axis corresponds to deciles based on market capitalization. The omitted decile is the lowest market-capitalization decile. (Color figure can be viewed at wileyonlinelibrary.com)

to 4.2% (columns (4) to (6)). By contrast, the effect on realized gross margin is not significant at any horizon. In Panel B, we split the independent variable by low and high number of incidents based on the median number of incidents in a given year. The effect is stronger when there is a high number of incidents in a year, consistent with our baseline regressions using analyst forecasts. The preceding analysis shows that firms' realized earnings and sales decrease after negative ESG incidents. This implies that analysts are correct when they downward-adjust their forecasts following negative ESG news.

To further elaborate on this point, we turn to analyst-level forecasts and ask whether reacting to ESG incidents makes analysts more accurate in their EPS forecasts. Specifically, we first collect individual analyst-level forecasts and forward-fill the forecasts to the monthly level to keep a similar data structure compared to consensus-level forecasts.[14] We then run the following regression using the analyst-firm panel:

$$\frac{|FEPS_{i,e,j,t} - EPS_{i,e}| - |FEPS_{i,e,j,t-1} - EPS_{i,e}|}{|EPS_{i,e}|} = \alpha + \eta DownwardAdj_{i,e,j,t}$$

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

$$+\beta DownwardAdj_{i,e,j,t} \times \mathbb{1}\{ESG\ incidents\ of\ firm\ i\ in\ [t-6, t]\}$$
$$+\gamma_{i,e,t} + \epsilon_{i,e,j,t}\ , \tag{8}$$

where $FEPS_{i,e,j,t}$ is the EPS forecast made for earnings announcement e of firm i by analyst j in month t,[15] $EPS_{i,e}$ is the realized earnings of firm i for earnings announcement e, $DownwardAdj_{i,e,j,t}$ is a dummy variable indicating whether analyst j downward-adjusts her EPS forecast from month $t-1$ to month t (i.e., $FEPS_{i,e,j,t} - FEPS_{i,e,j,t-1} < 0$), and $\gamma_{i,e,t}$ indicates firm × earnings announcement × month of forecast fixed effects. Intuitively, this regression compares analysts who issue EPS forecasts for the *same* firm's earnings announcement e in the *same* month, and tests whether the analysts who downward-adjust EPS forecasts following ESG incidents see a decline in their forecast error compared to analysts who do not downward-adjust their EPS forecasts.

The results are presented in Table XIV. The coefficient estimates on *DownwardAdj* are negative and significant, which captures the baseline effect that analysts are on average overoptimistic and any downward adjustment leads to a lower forecast error.[16] The coefficients on the interaction term are our coefficients of interest. They are negative and significant for annual forecasts and weakly significant for quarterly forecasts. This suggests that after negative ESG incidents, analysts who downward-adjust EPS forecasts decrease forecast error further than when there is no ESG incident, compared to analysts who do not downward adjust their EPS forecasts.

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

VII. Conclusion

Using a global sample, this paper examines how negative ESG news impacts the revisions of earnings forecasts by analysts. Following the occurrence of negative ESG incidents, we document significant downward revisions of earnings forecasts over both short horizons (from one quarter) and longer horizons (up to three years). These downward revisions are due largely to negative revisions of future sales forecasts, suggesting that analysts expect consumers to react negatively to deteriorating ESG performance. We also provide evidence that stock prices react negatively to the occurrence of negative ESG news. Interestingly, most of the negative impact on stock prices from these ESG news items is quantitatively explained by changes in earnings forecasts. Analysts are correct in making the forecast revision after ESG incidents. Analysts who

[15] Note that e denotes one specific firm-level earnings realization, for example, the earnings of fiscal year 2015.

[16] See, for example, Das, Levine, and Sivaramakrishnan (1998) for more detailed discussion on analysts' overoptimism.

Table XIV

Analyst-Level Forecast Revisions and Forecast Errors

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

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years
Downward Adjustment	−0.005***	−0.012***	−0.015***	−0.012***	−0.014***	−0.022***	−0.024***
	(−6.21)	(−9.92)	(−11.33)	(−9.33)	(−16.77)	(−19.76)	(−21.13)
>=1 incidents in months [t−6,t] × Downward Adjustment	−0.001	−0.002*	−0.002*	−0.003**	−0.002***	−0.003***	−0.004***
	(−0.91)	(−1.83)	(−1.79)	(−2.33)	(−2.84)	(−3.56)	(−3.98)
Firm × Earnings Announcement × Month	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.303	0.272	0.263	0.219	0.225	0.214	0.198
Obs.	2,656,113	2,222,054	1,741,710	860,246	8,693,747	7,434,766	3,248,309

downward-adjust forecasts decrease forecast errors compared to those who do not, suggesting that the integration of ESG concerns is rational rather than a "fad."

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

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Appendix: RepRisk versus Other ESG Data

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

To verify that, despite the reservations about ESG scores discussed above, there is indeed a link between RepRisk news and changes in ESG ratings, we compare the RepRisk news items with the scores provided by three of the most influential ESG rating agencies, namely, Refinitiv (previously Asset4), MSCI, and Sustainalytics. For Refinitiv, we use the "Equal-weighted Rating." For MSCI, we use "Industry Adjusted Score." For Sustainalytics, we use "Total ESG Scores." Note that Berg, Fabisik, and Sautner (2021) highlight the rewriting-history issue of Refinitiv. We nevertheless use Refinitiv scores as they are a widely used ESG data set. We regress the ESG scores defined at the monthly level and their logarithms on the logarithm of the number of incidents reported by RepRisk in the current and the preceding months,

$$ESG\,Score_{i,t} = \sum_{s=0}^{12} \beta_s log(num.\,ESG\,incidents_{i,t-s}) + \gamma_i + \delta_{t\times Industry} + \epsilon_{i,t}, \quad (9)$$

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 one plus the number of incidents in month $t-s$. We include 12 lags to account for the dynamic nature of the scores. We also include firm fixed effects since both the scores and the probability of observing ESG-related events are driven to a large extent by time-invariant firm characteristics. Finally, we include month $\times$ industry (GICS2) fixed effects in these regressions because the number of ESG-related news items is likely to exhibit different time patterns in different industries. We cluster the standard errors at the firm and month levels to account for possible dependence across firms and months.

The results, reported in Table A.I, show a clear connection between ESG scores and ESG-related news, with negative coefficients over all horizons and for all three scores considered. In all but three cases, the coefficients are also statistically significant at conventional levels. Comparing the results across score providers, we see that the results seem stronger, both economically and statistically, for the Asset4 and MSCI ratings than for the Sustainalytics ratings. The latter finding could suggest that ESG news-related data play a lesser role in the construction of Sustainalytics scores than in the construction of the scores from the other providers. Overall, the evidence presented in Table A.I is consistent with the view that the ESG incidents we consider in our study are part of the information set used by the providers of ESG scores.

Table A.I

ESG Incidents Predict ESG Scores

This table reports the results of a regression of ESG scores on ESG incidents. In columns (1) to (3), the dependent variables are the ESG scores from the different ESG data providers. In columns (4) to (6), the dependent variables are the natural logarithm of one plus the ESG scores. All the ESG scores are on a 0 to 100 scale. The independent variables are the natural logs of one plus the number of incidents in each of the past 12 months. The F-statistic and p-value are the results of a test for whether the sum of the coefficients is equal to zero. Standard errors are double-clustered at the firm and month levels. t-Statistics are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	ESG Score			log(ESG Score)		
	(1) Asset4	(2) MSCI	(3) Sustainalytics	(4) Asset4	(5) MSCI	(6) Sustainalytics
log(num. incidents) in month t	−0.740***	−0.807***	−0.040	−0.019***	−0.026***	−0.001**
	(−6.82)	(−6.21)	(−1.23)	(−5.55)	(−5.34)	(−2.32)
log(num. incidents) in month t−1	−0.736***	−0.791***	−0.087***	−0.019***	−0.024***	−0.002***
	(−6.91)	(−6.78)	(−2.68)	(−5.63)	(−5.76)	(−3.71)
log(num. incidents) in month t−2	−0.664***	−0.778***	−0.063**	−0.017***	−0.025***	−0.002***
	(−6.74)	(−6.99)	(−2.17)	(−5.47)	(−6.41)	(−3.14)
log(num. incidents) in month t−3	−0.679***	−0.800***	−0.053*	−0.018***	−0.023***	−0.001***
	(−6.83)	(−7.70)	(−1.91)	(−5.62)	(−6.15)	(−2.86)

(*Continued*)

Table A.I—*Continued*

	ESG Score			log(ESG Score)		
	(1) Asset4	(2) MSCI	(3) Sustainalytics	(4) Asset4	(5) MSCI	(6) Sustainalytics
log(num. incidents) in month t−4	−0.627***	−0.807***	−0.047*	−0.017***	−0.023***	−0.001***
	(−6.49)	(−7.95)	(−1.75)	(−5.32)	(−6.15)	(−2.73)
log(num. incidents) in month t−5	−0.615***	−0.855***	−0.068**	−0.017***	−0.025***	−0.001***
	(−6.18)	(−8.79)	(−2.37)	(−5.29)	(−6.90)	(−3.10)
log(num. incidents) in month t−6	−0.601***	−0.867***	−0.074**	−0.017***	−0.025***	−0.002***
	(−6.05)	(−9.10)	(−2.43)	(−5.24)	(−6.84)	(−3.05)
log(num. incidents) in month t−7	−0.635***	−0.850***	−0.064**	−0.019***	−0.024***	−0.001***
	(−6.33)	(−8.85)	(−2.12)	(−5.69)	(−6.52)	(−2.86)
log(num. incidents) in month t−8	−0.669***	−0.911***	−0.078**	−0.020***	−0.027***	−0.002***
	(−6.42)	(−9.20)	(−2.60)	(−5.92)	(−6.97)	(−3.32)
log(num. incidents) in month t−9	−0.750***	−0.953***	−0.079**	−0.022***	−0.027***	−0.002***
	(−6.76)	(−9.45)	(−2.41)	(−6.41)	(−6.75)	(−3.26)
log(num. incidents) in month t−10	−0.769***	−1.018***	−0.076**	−0.023***	−0.030***	−0.002***
	(−6.88)	(−9.45)	(−2.07)	(−6.65)	(−7.13)	(−2.89)
log(num. incidents) in month t−11	−0.859***	−1.075***	−0.105***	−0.026***	−0.031***	−0.002***
	(−7.27)	(−9.55)	(−2.70)	(−7.32)	(−7.15)	(−3.46)
log(num. incidents) in month t−12	−0.906***	−1.167***	−0.147***	−0.028***	−0.032***	−0.003***
	(−7.14)	(−9.31)	(−3.43)	(−7.55)	(−6.67)	(−4.16)
Month * Industry FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Sum of Coef.	−9.250	−11.680	−0.982	−0.261	−0.341	−0.023
F-stat	150.662	95.884	9.443	188.172	64.558	16.778
p-value	0.000	0.000	0.003	0.000	0.000	0.000
Adj. R^2	0.889	0.767	0.903	0.867	0.674	0.904
Obs.	325,458	281,059	184,332	325,458	281,059	184,332

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Appendix S1: Internet Appendix.
Replication Code.