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ESG Incidents and Analyst Reactions: The Impact of SASB Materiality Standards on Price Target Forecasts

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ABSTRACT

This paper investigates differences in financial analysts reaction to ESG risks before and after the introduction of SASB materiality accounting standards. Using RepRisk data for S&P 500 firms and the staggered release of the SASB materiality classifications between 2013 and 2016 as shocks to sustainability disclosure, we analyze the influence of ESG incidents on analyst price targets. We show that such events significantly impact analyst responses, yet there is a positive shift in analysts' reaction to not material ESG incidents after the introduction of SASB standards. The paper suggests that when accounting standards emphasize topics intended to benefit investors, they can create an important downside by eliminating the negative reaction of financial analysts to not material ESG incidents in their price targets forecasts.

JEL classification: G14, M14

Keywords: Environmental, Social, and Governance (ESG) risks, Analyst price targets, Materiality, Accounting standards, Greenwashing

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1 Introduction

The time when environmental, social and governance (ESG) issues were the niche concern of a select group of ethical or socially responsible investors is long gone. The ESG acronym first came to light in the Freshfields Report titled A Legal Framework for the Integration of Environmental, Social and Governance Issues into Institutional Investment in October 2005. The report argued that "integrating ESG considerations into an investment analysis so as to more reliably predict financial performance is clearly permissible and is arguably required in all jurisdictions." Investment practices have undergone a significant shift, thanks to the rise of responsible investment proponents such as the United Nations Principles for Responsible Investment (PRI). Investors have been encouraged to incorporate ESG factor analysis into their decision-making processes in order to enhance returns and better manage risks.

In 2020, almost 36 percent of total assets under management globally were labelled sustainable investment, including those of many public pension funds (Global Sustainable Investment Alliance (GSIA), 2021). The world's largest asset management company, BlackRock, publicly stated in 2018 that ESG issues are essential to long-term value creation (Sorkin, 2018). Larry Fink, the CEO of BlackRock, stated in his annual letter to chief executives in 2020, that the investment firm would step up its consideration of climate change in its investment considerations because it was reshaping the world's financial system.

Concerns over climate change and what it might entail for long-term investment value and returns have resulted in initiatives such as Climate Action 100+, the Net-Zero Asset Owners Alliance, and most recently the Glasgow Financial Alliance for Net Zero, where many (although far from all) institutional investors have come together to put pressure on companies to take the necessary action on climate change (Dzielinski et al., 2022).

In the light of existing ESG hype, financial materiality has become a cornerstone of accounting standards aimed at aligning corporate sustainability practices with investor interests. A topic is defined as financially material (in other words, relevant or useful) on industry level if it most likely affects cash flows, access to finance and cost of capital. Standards such

as those introduced by SASB emphasize material ESG topics to guide firms in disclosing information that is most relevant to financial stakeholders. While this approach enhances transparency and focuses managerial efforts on investor-prioritized issues, it also creates unintended consequences. Recent findings suggest that sustainability-related incidents decrease for topics classified as material by SASB, highlighting firms' strategic responses to prioritize these issues (Goettsche et al., 2023). However, this improvement comes at the expense of increased incidents for non-material topics, reflecting a shift in attention and resources away from broader sustainability goals. These dynamics raise concerns about the unintended trade-offs inherent in materiality-based standards and their broader implications for corporate behavior and market perceptions. One significant downside could also be the potential elimination of financial analysts' negative reactions to non-material ESG incidents in their price target forecasts, which may reduce the accountability of firms for such events. Elaborating on this concern, this paper studies the impact of SASB materiality standards on analyst price targets following ESG incidents.

The paper is structured in the following way: the second chapter introduces the background and the literature; the third chapter describes the data and the descriptive statistics; the fourth part examines the results; the fifth part represents the conclusion.

2 Background and Literature

This section sheds light on the prior studies, which examine market and analysts' reactions to ESG events, as well as the impact of SASB materiality standards introduction on ESG incidents.

The research question regarding the impact of SASB materiality standards on analyst price targets following ESG incidents has not been directly addressed in the current literature. At the same time, previous studies have emphasized some useful metrics to examine market and analysts' reactions to ESG events. As for the market perspective, market reactions to

ESG events or news have been explored in prior studies by Flammer (2013), Dimson et al. (2015), Krüger (2015); Capelle-Blancard and Petit (2019) (use an original database provided by Covalence Ethical Quote), Grewal et al. (2019), Naughton et al. (2019), and Gibson et al. (2020). For example, Khan et al. (2016) found that positive (negative) ESG news are associated with more positive (negative) stock price reactions. Authors measure stock reactions as the industry (six-digit GICS) adjusted stock returns on the three-day window between one day before and after the ESG news, which is constructed using Compustat and CRSP. Their total sample includes 31,854 unique firm–day observations with ESG news from TruValue Labs Pulse between January 2010 and June 2018.

Glossner (2021) concludes that high ESG incident rates predict more pronounced negative stock returns in firms with more short-term ownership, higher analyst forecast dispersion, and lower analyst coverage. The author performs an event study, where every event indicates that a firm had one or more ESG incidents in that month. For every event, Glossner (2021) estimates the firm's normal stock returns in a pre-event window ranging from 299 trading days to 50 trading days prior to the event. In order to estimate the coefficients of the pre-event regression the author uses the four-factor Carhart (1997) market model and the corresponding 48-industry portfolio from Fama and French (1997). Using saved coefficients from the pre-event regression, Glossner (2021) calculates the event's cumulative abnormal return (CAR) during the event window covering either 21 or 31 trading days. The following formula is used to calculate the t-statistic for the CARs:

$$t(CAR) = \frac{\frac{1}{N}\sum_{n=1}^{N} CAR_n}{\sqrt{\frac{1}{N^2}\sum_{n=1}^{N} Var(CAR_n)}}, \tag{1}$$

where N is the number of events and $Var(CAR)$ stands for the variance of the residuals of the pre-event regression multiplied by the number of trading days in the event window.

As for the analyst's perspective, there have been numerous studies to investigate on how analysts change their forecasts relative to ESG events. For example, Derrien et al.

(2021) find that negative ESG news would lead analysts to significantly decrease their prior earnings forecasts. The researchers collect monthly analyst consensus forecasts of earnings per share (EPS) and price targets (PTGs) from the Institutional Brokers Estimate System (IBES) database. EPS forecasts are issued over 1-quarter, 2-quarter, 3-quarter, 4-quarter, 1-year, 2-year, and 3-year horizons, while the price targets (PTGs) represent the projected price level within a specific time horizon forecasted by the analysts and was restricted in their sample to PTGs for 12 months. Derrien et al. (2021) use also ESG incidents data from RerRisk and match it with the monthly IBES consensus forecasts, aggregating all the RepRisk ESG incidents that occurred between two summary statistic dates to the monthly level. Their analysis focuses on changes in forecasts. For EPS forecast F_tEPS_{t+h} made in month t for horizon h, they define the change in the EPS forecasts between months t and $t-1$ as following:

$$\Delta F_tEPS_{t+h} = \frac{F_tEPS_{t+h} - F_{t-1}EPS_{t+h}}{abs(F_{t-1}EPS_{t+h})}, \tag{2}$$

where the authors scale the forecast change by the absolute value of the initial forecast to address negative forecasts. Similarly, Derrien et al. (2021) define the change in PTGs using the following formula:

$$\Delta PTG_t = \frac{PTG_t - PTG_{t-1}}{PTG_{t-1}}. \tag{3}$$

In addition to CARs following ESG incidents, Glossner (2021) explores how negative news are associated with analyst earnings surprises, which are defined as the difference between the actual earnings per share for fiscal year t and the median IBES analyst forecast, scaled by the stock price at the end of fiscal year t. The author estimates the consensus forecast for the end of the fiscal year eight months earlier. The ESG incident rates from RepRisk are measured 12 months prior to the fiscal year-end, which is four months in advance to the estimates made by the analysts.

The paper by Goettsche et al. (2023) explores the real effects of the SASB's materiality classifications on sustainability performance. The authors examine how the introduction

of SASB materiality standards influences firms' resource allocation toward material versus immaterial ESG topics. They find that while firms improve their performance on material topics after the release of the standards, their performance on immaterial topics deteriorates. This creates a double-edged effect where investor-aligned disclosure improvements occur at the expense of broader sustainability progress. These findings extend the literature on the unintended consequences of materiality-based standards, contributing to ongoing debates on the role of sustainability disclosure in shaping firm behavior and stakeholder outcomes. This work provides a valuable backdrop for understanding the nuanced impacts of sustainability-focused regulations like SASB standards, particularly in the context of analyst reactions to ESG risks.

To summarize, a large number of existing studies in the broader literature has examined the reactions to ESG events from the market and analysts' perspective. While there is an existing study on the real effects of the SASB's materiality classifications on sustainability performance, a research question regarding the impact of SASB materiality standards on analyst price targets following ESG incidents remains to be addressed.

3 Data and Descriptive Statistics

This paper focuses on testing the following hypotheses, which are listed in the table below.

The empirical part of this paper starts with the description of the data. We examine the relation between the ESG incidents from RepRisk and the market and analysts' reaction to these events. This empirical setting is aiming at defining the impact of SASB materiality standards on analyst price targets following ESG incidents. The sample includes observations for companies, which were members of the S&P 500 between the years 2007 to 2020. The RepRisk data is available starting from January 2007, while the restriction of the dataset till the beginning of 2020 is due to covid-19 pandemic, which can affect the results. The dependent variables is the change in analysts' forecasts. To capture the impact of ESG, we

Table 1: Defining Research Hypotheses

Hypothesis	*Topic*
H1: ESG incidents are associated with negative market reaction	Market reaction
H2.1: Total/severe/reach/novel ESG incidents are associated with lower percentage changes in recommended prices by the same analyst	Analyst level
H2.2: Environmental/social/governance incidents are associated with lower percentage changes in recommended prices by the same analyst	Analyst level
H3: SASB regulation brought new information to analysts regarding the financial materiality of ESG incidents	Analyst level

use ESG incidents from RepRisk , which are used in this paper as a independent variable. Additionally, we use the mean and sum of Cumulative Abnormal Returns in a [-1,1] window around RepRisk incidents between two closest price target changes for the same analyst. The data on control variables from the year 2007 to 2020 are obtained from the Compustat database.

3.1 Market and Analysts' Reaction

The cumulative abnormal returns of the Fama & French Plus Momentum model during the one-day window around ESG news are obtained to perform the event study with the help of Wharton Research Data Services (WRDS), where we uploaded txt files with incident dates and cusip numbers for S&P 500 companies. The data are collected to test H1.

As for analysts' reaction, we calculate price targets (PTGs) changes for the same analyst between two closest forecasts. The metric described below is used in testing H2 and H3. The changes in PTGs forecasts between two closest forecasts of the same analyst (t and $t-1$) is defined as following:

$$\Delta PTG_t = \frac{PTG_t - PTG_{t-1}}{PTG_{t-1}}. \tag{4}$$

Percentage changes in analysts' price targets forecasts are calculated based on the data from I/E/B/S database. The data on ESG incidents are obtained from RepRisk and is matched with the I/B/E/S dataset.

RepRisk is a Zurich-based provider of ESG data. RepRisk performs daily analysis of the information from public sources in 23 languages and records negative ESG-related incidents at the firm level. The data are available starting from 2007 year. RepRisk classifies ESG incidents in accordance with 28 distinct issues. Environmental issues include news about climate change, GHG emissions, pollution, waste issues, animal mistreatment etc. Social issues cover child labor, human rights abuses, discrimination in employment etc. Governance issues include executive compensation issues, corruption, fraud, tax evasion etc. Cross-cutting issues cover controversial products and services, supply chain issues, violation of national legislation etc. Since one incident can be associated with multiple issues, it can, therefore, belong to two or more E/S/G categories. Table 1 shows the distribution of incident types for S&P 500 companies. Approximately one third of the incidents are associated with two or more E/S/G categories. It should be noted that there are also 6184 cross-cutting incidents, which are associated with none of the E/S/G categories included in the Table 1.

Figure 2 shows the average number of monthly incidents by year for S&P 500 companies. The number of ESG incidents counted by RepRisk has grown over time. Events related to social issues are the most frequent in the RepRisk data for S&P 500 companies. At the beginning of the sample period, there are more environmental than governance incidents, while starting from 2012 year, there are more governance incidents than environmental.

Figure 3 demonstrates the average number of monthly incidents by year for S&P 500 companies for material and not material ESG incidents. It might be inferred that the number of not material ESG incidents has grown over time, which is in line with Goettsche et al. (2023), who infer that sustainability-related incidents decrease after the release of SASB classifications indicating relevant topics for investors but, conversely, sustainability-related incidents increase for SASB classifications indicating non-relevant topics. Figure 4 shows the

Table 2: Distribution of ESG incidents by type for S&P 500 companies

E	*S*	*G*	*# incidents*	*Percent*
1	0	0	4700	10.86%
0	1	0	11989	27.69%
0	0	1	13999	32.33%
1	1	0	7352	16.98%
1	0	1	862	1.99%
0	1	1	2233	5.16%
1	1	1	2161	4.99%

average number of monthly incidents by year for S&P 500 companies for material and not material ESG incidents by E, S, and G pillars.

In order to analyze the distribution of RepRisk events by industry, the data on RepRisk events is merged with the sectoral data from Compustat. Figure 5 illustrates the monthly average number of incidents by sector, which are defined according to GICS classification. The highest number of monthly ESG incidents is reported in financial sector, which consists of such industry groups as Banks, Diversified Financials, and Insurance. The second highest number of ESG incidents is represented by Consumer Discretionary sector, consisting of Automobiles & Components, Consumer Durables & Apparel, Consumer Services, and Retailing. This sector is followed by Consumer Staples (Food & Staples Retailing, Food, Beverage & Tobacco, Household & Personal Products).

The number of RepRisk incidents is calculated on the analyst level between two closest price target changes for the same analyst. While Derrien et al. (2021) uses monthly consensus on price targets (an aggregated measure for all analysts), our metric allows to capture the number of RepRisk incidents prior to a price target change made by the same analyst. We exclude the observations of pairs of an analyst and a company if the analyst provided less than 3 price target forecasts for this company. We also calculate the number of days to the previous price target change by the same analyst and control for this metric in our regressions. The observations are excluded in case the time between two price target changes

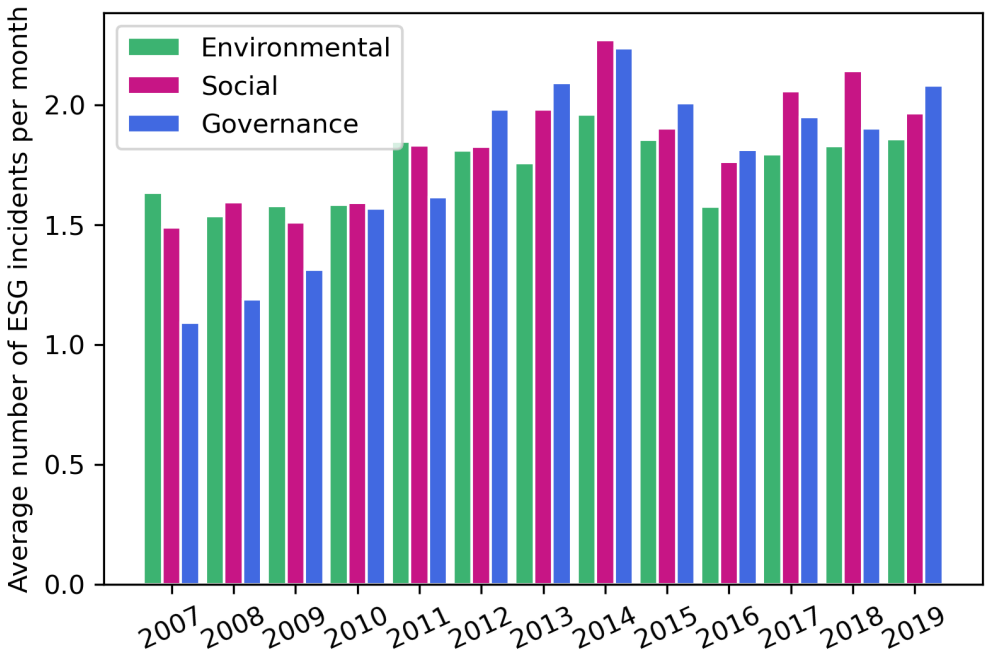

Figure 1: Number of RepRisk ESG incidents by year for S&P 500 companies

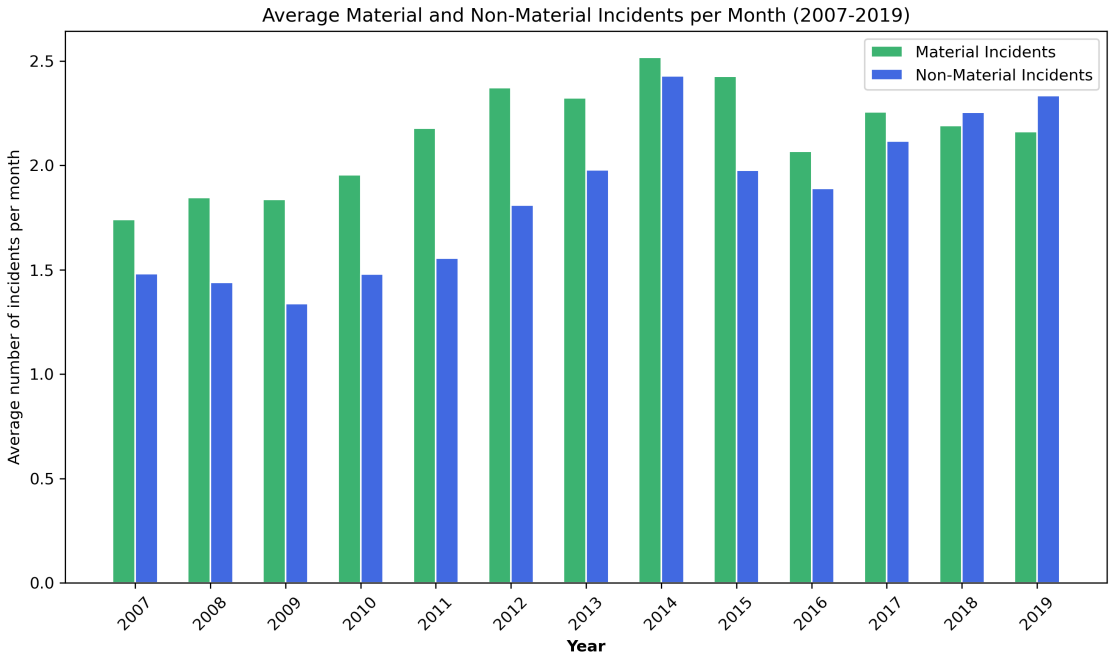

Figure 2: Number of material and not material RepRisk ESG incidents by year for S&P 500 companies

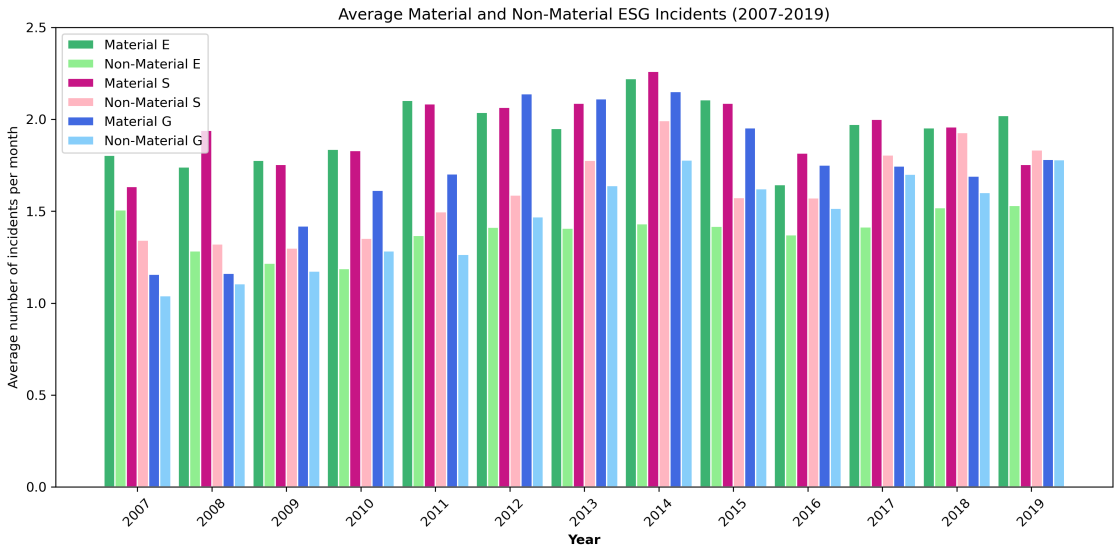

Figure 3: Number of material and not material RepRisk ESG incidents by pillar by year for S&P 500 companies

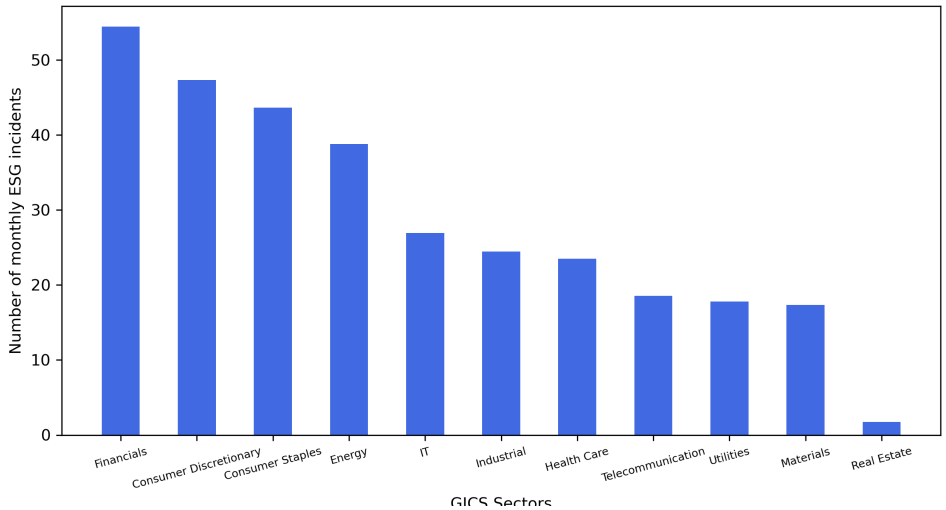

Figure 4: Number of incidents by GICS sector for S&P 500 companies

by the same analyst is more than one year. We show the timing of ESG incidents and price target changes on analyst level in the Figure 6.

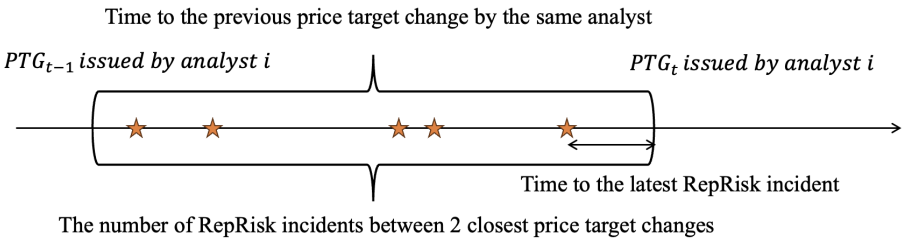

Figure 5: Timing of ESG incidents and price target changes on analyst level

In order to define whether severe, reach, and novel ESG incidents affect stronger the change in analysts' forecasts, such metrics as total amount of severe, reach, and novel incidents are calculated.

The severity score provided by RepRisk ranges from 1 to 3, where 1 indicates low severity, 2 stands for medium severity, and 3 denotes high severity. The severity (harshness) is defined in a rule-based way as a function of the alleged violation of national laws and international standards along three dimensions: the consequences of the risk incident, the extent of the risk incident, and whether the incident is caused by an accident, by negligence, by intent, or in a systematic way. Only risk incidents with severity above 2 were counted for the purposes of the construction of the total severe incidents variable. Reach of RepRisk incidents varies from 1 to 3 and is based on readership/circulation (e.g., local media, national and regional media or international media). Novelty is a dummy variable that distinguishes re-occuring or new issues.

Following the approach used by Glossner (2021) in his paper, we calculate the logarithm of the total number of incident news over the same period as follows: natural logarithm of 1 + number of ESG incidents. Similarly, logarithms of the total number of severe, reach, and novel incidents are calculated. We also look at the ESG pillars separately and calculate the number of environmental, social, and governance incidents between the price target changes issued by the same analyst.

Table 3: Descriptive Statistics

Variable	*N*	*Mean*	*Median*	*SD*	*Min*	*P25*	*P75*	*Max*
ESG characteristics for the market reaction								
Severity of ESG Incidents	26,693	1.365	1.000	0.513	1.000	1.000	2.000	3.000
ESG characteristics on analyst level								
Log Number Total Incidents	205225	0.624	0.000	0.870	0.000	0.000	1.099	3.584
Log Number Severe Incidents	205225	0.304	0.000	0.561	0.000	0.000	0.693	2.398
Log Number Reach Incidents	205225	0.189	0.000	0.475	0.000	0.000	0.000	2.398
Log Number Novel Incidents	205225	0.350	0.000	0.566	0.000	0.000	0.693	2.303
Log Number Environmental Incidents	205225	0.261	0.000	0.540	0.000	0.000	0.000	2.485
Log Number Social Incidents	205225	0.398	0.000	0.687	0.000	0.000	0.693	2.944
Log Number Governance Incidents	205225	0.302	0.000	0.589	0.000	0.000	0.693	2.708
Log Number Material Incidents	205225	0.388	0.000	0.686	0.000	0.000	0.693	2.944
Log Number Not Material Incidents	205225	0.236	0.000	0.447	0.000	0.000	0.406	3.584
Analyst level								
Price Targets Change Same Analyst (ΔPTG)	205225	0.023	0.028	0.119	-0.324	-0.043	0.083	0.409
Time to Previous Price Target Change (*Days*)	205225	91	74	85	2	34	103	461
Average of CARs	205225	0.000	0.000	0.015	-0.448	0.000	0.000	0.435
Sum of CARs	205225	-0.001	0.000	0.049	-1.818	0.000	0.000	1.059
Control variables on the analyst level								
Log Market Cap	205225	10.003	9.873	1.099	6.338	9.250	10.625	13.886
Tobin Q	205225	2.344	1.902	1.487	0.626	1.387	2.730	35.614

* Note: *Severity of ESG Incidents* is obtained from RepRisk and ranges from 1 to 3, where 1 indicates low severity, 2 stands for medium severity, and 3 denotes high severity. *Log Number Total/Severe/Reach/Novel Incidents*, *Log Number Environmental/Social/Governance Incidents*, *Log Number Material/Not MaterialIncidents*, *Log Environmental Incidents in* $[t-2,t]_{i,t}$ *and* $[t-4,t-2]_{i,t}$, and *Abnormal Environmental Incidents in* $[t-2,t]_{i,t}$ are calculated based on the data from RepRisk and SASB materiality finder for material and not material incidents. *Cumulative Abnormal Returns* ($CARs$) is calculated for each ESG incident using WRDS event study service. *Price Targets Change Same Analyst* (ΔPTG) is calculated on firm-analyst level based on the data from I/B/E/S database as the difference between the two closest price target changes by the same analyst divided by the previous price target.

In order to calculate material and not material ESG incidents, we refer to the SASB materiality finder.

3.2 Descriptive Statistics

This subsection is devoted to the descriptive statistics for the main variables that are described above.

4 Empirical Analyses

4.1 Market Reaction

Market reaction to RepRisk ESG incidents is explored through the U.S. Daily Event Study by WRDS, where incidents are restricted for the set of S&P 500 companies from 2007 till the beginning of 2020. For the purposes of this analysis, an estimation window, which stands for length of the time period (in trading days) used to estimate the expected return and residual return variable, is set as 100 days. The minimum number of non-missing return observations within the estimation window required to produce estimates of expected return is equal 70. The number of trading days to be established between the end of the estimation window and the beginning of the event window is 50. The event study is performed for the event window of ± 1, meaning that the event window starts/ends 1 trading day before/after the event occurrence. The first hypothesis implies that ESG incidents are associated with negative market reaction.

The results of the event study with the event window of ± 1 for all incidents, sharp, and severe incidents are presented in the Table 4. Figures 6-8 show cumulative abnormal return (mean and 95% confidence limits). It might be inferred that for all settings the mean cumulative abnormal return is positive one trading day before the event, while it turns to negative on the day of event occurrence and gets even more negative one on the next trading day after the incident. Interestingly, the largest negative effect is reported for severe incidents on both the day of the event occurrence and on the following day.

Additionally, the *severity of ESG incidents* is regressed on the cumulative abnormal returns ($CARs$) on the day following incident date:

$$CAR_t = \beta_0 + \beta_1 Severity\ of\ ESG\ Incidents_{i,t} + Controls + Year\ FE + Industry\ FE + \varepsilon_{i,t}, \tag{5}$$

where control variables include $MarketCap$ and $TobinQ$, as well as year and industry fixed

Table 4: Results of the event study with the event window of ±1 for S&P 500 companies

Day Relative to Event	*Mean CARs (all incidents), %*	*Mean CARs (sharp incidents), %*	*Mean CARs (severe incidents), %*
-1	0.006865	0.000506	0.000293
0	-0.030502	-0.038679	-0.051329
1	-0.040797	-0.047686	-0.063947

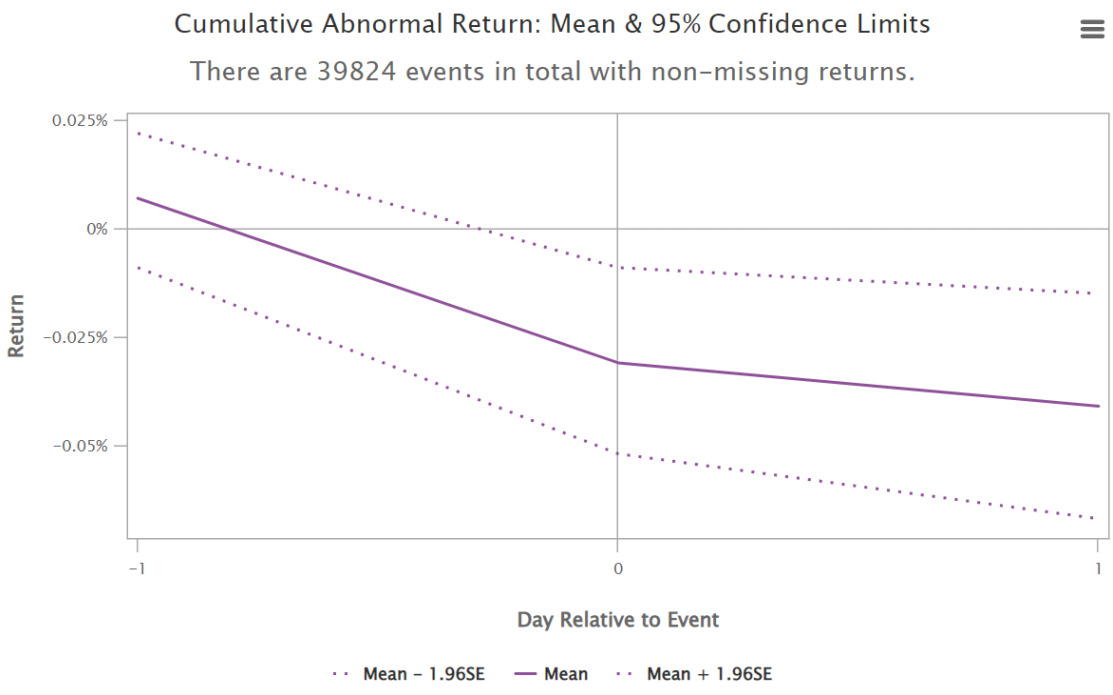

Figure 6: Cumulative Abnormal Return (mean and 95% confidence limits) for all incidents

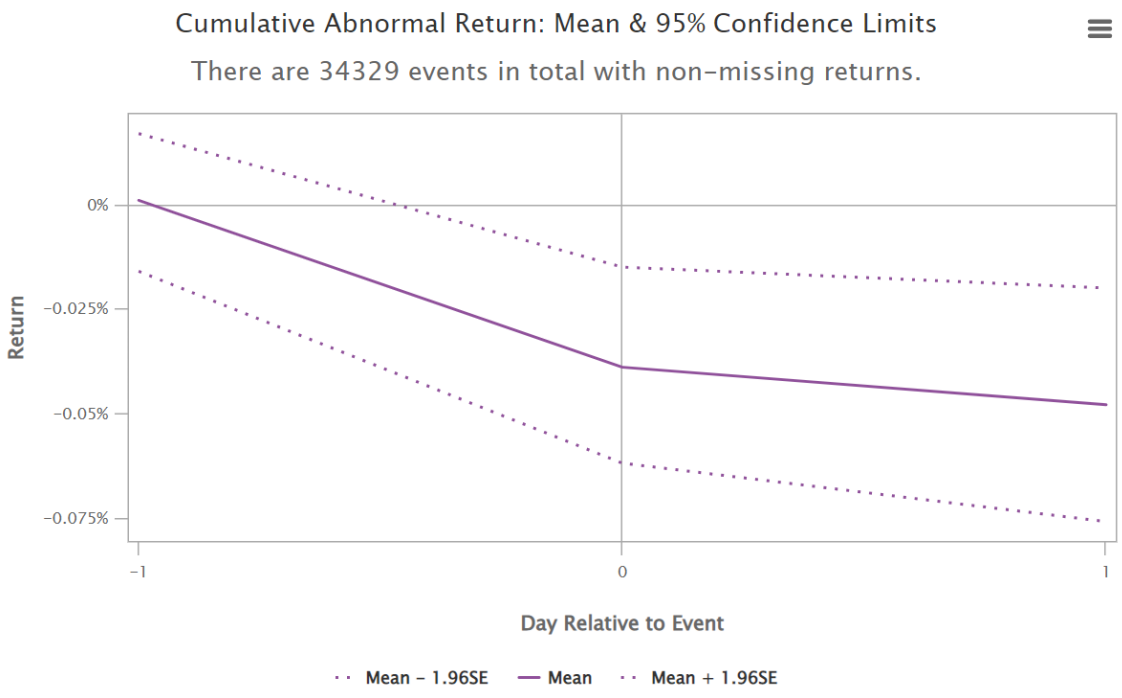

Figure 7: Cumulative Abnormal Return (mean and 95% confidence limits) for sharp incidents

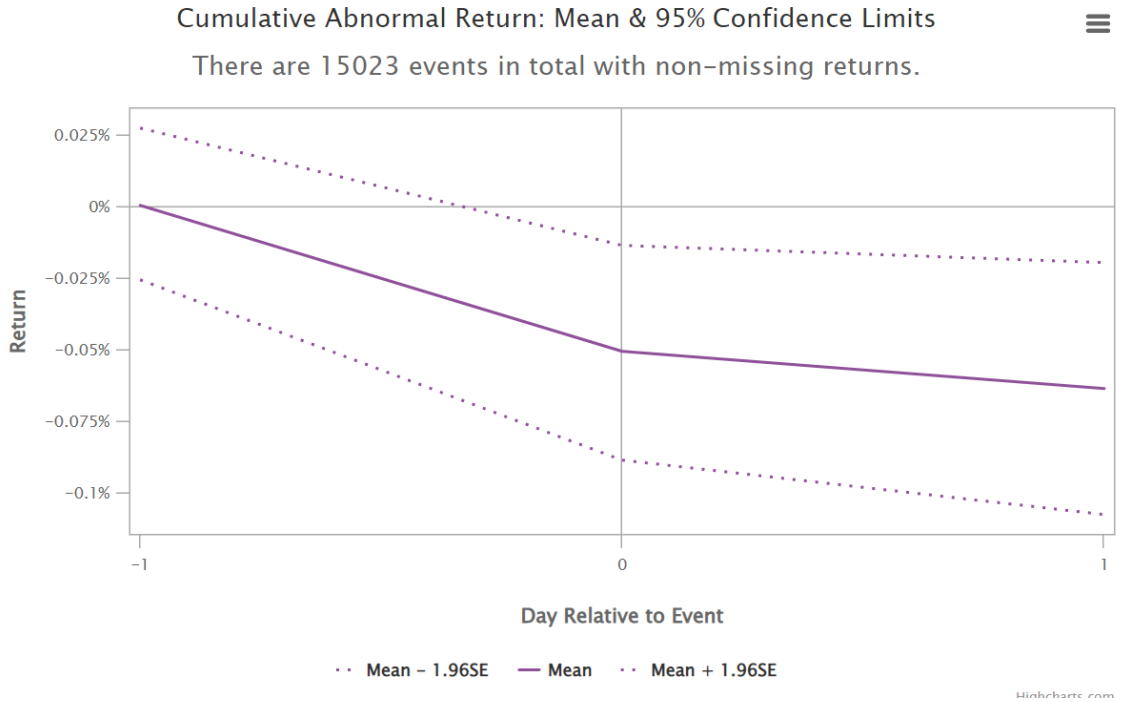

Figure 8: Cumulative Abnormal Return (mean and 95% confidence limits) for severe incidents

Table 5: Estimates of Eq. (15)

	$CAR_t(1)$	$CAR_t(2)$
Severity of ESG Incidents	-0.00061* (0.05494)	-0.00064** (0.04382)
Observations	26,693	26,693
R-squared	0.00497	0.00609
Controls	No	Yes
Fixed Effect	Year & Industry	Year & Industry

* Note: The values presented in this table show the coefficient followed by the p-value in brackets for each variable. '***', '**', and '*' correspond to significance at the 0.01, 0.05, and 0.1 level. OLS regression for equation 15. The dependent variable is cumulative abnormal returns ($CARs$), which is calculated for each ESG incident using WRDS event study service. *Severity of ESG Incidents* ranges from 1 to 3, where 1 indicates low severity, 2 stands for medium severity, and 3 denotes high severity. The severity (harshness) is defined in a rule-based way as a function of the alleged violation of national laws and international standards along three dimensions: the consequences of the risk incident, the extent of the risk incident, and whether the incident is caused by an accident, by negligence, by intent, or in a systematic way. Controls include *TobinQ* and *Logarithm of Market Cap*.

effects are included. In this setting, it is tested whether severity is associated with lower $CARs$:

β_1 in equation (15) < 0.

Table 5 demonstrates the results of regression *severity of ESG incidents* on cumulative abnormal returns ($CARs$) on the day following the date of the incident. The severity (harshness) of an incident is negatively associated with $CARs$, meaning that more severe ESG incidents imply lower $CARs$.

4.2 Analyst Level

Analysts' reaction reflected in change in price targets forecasts made by the same analyst is explored using the detailed data on price targets from I/B/E/S database. The dataset was restricted to observations related to S&P 500 companies from 2007 till 2020.

In this setting independent variables are *Log Number Total/Severe/Reach/Novel Incidents*, *Log Number Environmental/Social/Governance Incidents*, and *Log Number Material/ Not Material Incidents*. These variables are regressed on the *Price Targets Change Same*

Analyst (ΔPTG).

$$\Delta PTG_{it} = \beta_0 + \beta_1 Log\ Number\ of\ Total/Severe/Reach/Novel\ ESG\ Incidents_{it} + Controls + Firm\ FE + Year\ FE + \varepsilon_{it}, \tag{6}$$

$$\Delta PTG_{it} = \beta_0 + \beta_1 Log\ Number\ Environmental/Social/Governance\ Incidents_{it} + Controls + Firm\ FE + Year\ FE + \varepsilon_{it}, \tag{7}$$

$$\Delta PTG_{it} = \beta_0 + \beta_1 Log\ Number\ Material\ ESG\ Incidents_{it} \times SASB\ Treatment + \beta_2 Log\ Number\ Not\ Material\ ESG\ Incidents_{it} \times SASB\ Treatment + Average/Sum\ of\ CARs + Controls + Firm\ FE + Year\ FE + \varepsilon_{it}, \tag{8}$$

In this setting, firm fixed effects are included since the number of ESG events varies significantly across firms and is explained by time-invariant firm characteristics, as well as year and industry fixed effects. The set of control variables includes *Logarithm of Market Cap*, *Tobin Q* and *Time to Previous Price Target Change* (*Days*).

The second hypothesis that more total/severe/reach/novel ESG incidents, as well as more environmental/social/governance incidents, are associated with lower percentage changes of recommended prices on analyst level implies testing the following conditions based on the equations (16) and (17):

β_1 in equation (6) < 0,

β_1 in equation (7) < 0.

To test the hypothesis that SASB regulation brought new information to analysts regarding the financial materiality of ESG incidents we look at the β coefficients in equation (18) to see the change in the sign and significance of material and not material ESG incidents

before and after the SASB treatment. Additionally, we add *Average/Sum of CARs* as one of the independent variables to test if the effect of the analyst reaction is still in place in case of controlling for the market reaction.

The results of regressing the number of ESG incidents on change in forecasts of price targets by on the analyst level (see Table 6) demonstrate that the *Log Number Total Incidents* negatively affects the change in the forecasts. In other words, more ESG incidents lead to negative (or less positive) change in price targets by the same analyst. These results are quite meaningful, taking into account the fact that ESG incidents contain some negative information, which might negatively affect prices. While in the setting with the *Log Number Total Incidents* the coefficient is significant on the level of 0.01, the *Log Number Severe Incidents* is significant on the level of 0.05. In other words, the restriction for severe incidents with the level of severity above 2 helps capture the harshness of the incidents, which is reflected in more negative changes of price targets forecasts. The coefficient of the *Log Number Reach Incidents* is not significant, indicating that analysts rely on all type of sources to identify negative ESG news (local, national, regional, and international media). Novelty of ESG incidents matters for the analysts on the same level of significance as total ESG incidents.

Table 7 presents the results of regressing logarithms of environmental, social, and governance incidents separately on the change in price targets forecasts on firm-analyst level. Interestingly, the effect is significant on the 0.1 level for total and environmental incidents, on the 0.001 level for social incidents, while the coefficient for governance incidents is not statistically significant. In line with findings of Glossner (2021), governance incidents imply the lowest relevance.

Table 8 and Table 9 present the results of the staggered difference-in-difference regression for material and not material ESG incidents before and after the SASB treatment (the introduction of the SASB materiality standards in 2013-2016 depending on the industry) on the change in price target by the same analyst. In the first table the mean of Cumulative

Table 6: Estimates of Eq. (6)

	ΔPTG (1)	ΔPTG (2)	ΔPTG (3)	ΔPTG (4)
Log Number Total Incidents	-0.00179*			
	(-1.67690)			
Log Number Severe Incidents		-0.00343**		
		(-2.11530)		
Log Number Reach Incidents			-0.00174	
			(-0.89170)	
Log Number Novel Incidents				-0.00257*
				(-1.73980)
Observations	205225	205225	205225	205225
Adjusted R-squared	0.06446	0.06454	0.06442	0.06448
Controls	Yes	Yes	Yes	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year

* Note: The values presented in this table show the coefficient followed by the t value in brackets for each variable. '***', '**' and '*' correspond to significance at the 0.01, 0.05, and 0.1 level. OLS regression for equation 16. The dependent variable is percentage change in price targets forecasts on the analyst level, which is calculated for two closest price target changes for the same analyst as the difference between price after and price before divided by the price before. *Log Number Total/Severe/Reach/Novel Incidents* are calculated using based on the data from RepRisk. Controls include *TobinQ*, *Logarithm of Market Cap*, and *Time to Previous Price Target Change* (*Days*).

Table 7: Estimates of Eq. (7)

	ΔPTG (1)	ΔPTG (2)	ΔPTG (3)	ΔPTG (4)
Log Number Total Incidents	-0.00179*			
	(-1.67690)			
Log Number Environmental Incidents		-0.00277*		
		(-1.83920)		
Log Number Social Incidents			-0.00387***	
			(-2.81780)	
Log Number Governance Incidents				0.00079
				(0.55400)
Observations	205225	205225	205225	205225
Adjusted R-squared	0.06446	0.06448	0.06463	0.06440
Controls	Yes	Yes	Yes	Yes
Fixed Effect	Firm & Year	Firm & Year	Firm & Year	Firm & Year

* Note: The values presented in this table show the coefficient followed by the t value in brackets for each variable. '***', '**' and '*' correspond to significance at the 0.01, 0.05, and 0.1 level. OLS regression for equation 17. The dependent variable is percentage change in price targets forecasts on the analyst level, which is calculated for two closest price target changes for the same analyst as the difference between price after and price before divided by the price before. *Log Number Total/Environmental/Social/Governance Incidents* are calculated using based on the data from RepRisk. Controls include *TobinQ*, *Logarithm of Market Cap*, and *Time to Previous Price Target Change* (*Days*).

Abnormal Returns in [-1,1] window around RepRisk incidents between two closest price target changes for the same analyst is used as one of the independent variables. The results are robust if using the sum of Cumulative Abnormal Returns for the same period, which are presented in the second table. In the first table (if using the mean of CARs as one of the independent variables), the coefficients for the *Material/Not Material ESG Incidents* are negative and significant on 0.01 level before the SASB treatment, while the coefficient for *Material ESG Incidents* is not statistically significant after the SASB treatment and the coefficient for *Not Material ESG Incidents* is positive and statistically significant after the SASB treatment. These findings indicate that analysts react negatively to both material and not material ESG incidents. After the SASB materiality introduction, there is no change in their reaction to material incidents, and there is a positive change in not material incidents (analyst may also learn that some incidents that they thought of as material are not financially material incidents from the SASB introduction). SASB introduction has a negative effect since it results in positive reaction to not material incidents. The inclusion of the mean and the sum of Cumulative Abnormal Returns, representing the market reaction, helps to indicate the reaction of financial analysts, which is not captured by the market reaction.

Table 8: Estimates of Equation (8) with average CARs as one the independent variables

	ΔPTG (1)	ΔPTG (2)	ΔPTG (3)
Material ESG Incidents	-0.00402***		-0.00389***
	(-4.523)		(-4.372)
Not Material ESG Incidents		-0.00392**	-0.00430***
		(-3.073)	(-3.348)
SASB Treatment	-0.01938***	-0.02059***	-0.02112***
	(-11.692)	(-12.515)	(-12.419)
Material ESG Incidents × *SASB Treatment*	0.00169		0.00126
	(1.775)		(1.318)
Not Material ESG Incidents × *SASB Treatment*		0.00655***	0.00669***
		(4.523)	(4.591)
Average CARs	0.74657***	0.74794***	0.74715***
	(36.890)	(36.959)	(36.920)
Observations	205,225	205,225	205,225
Adjusted R^2	0.05955	0.05954	0.05964
Controls	Yes	Yes	Yes
Fixed Effects	Firm & Year	Firm & Year	Firm & Year

Note: Coefficients are followed by t-values in parentheses. '***', '**', and '*' indicate significance at levels of 0.01, 0.05, and 0.1, respectively.
OLS regression for equation 18. The dependent variable is the percentage change in price target forecasts on the analyst level, which is calculated for two closest price target changes for the same analyst as the difference between the price after and the price before divided by the price before. *Material/Not Material ESG Incidents* are calculated using RepRisk data. The materiality of ESG incidents is defined based on the SASB materiality finder. *Average CARs* is calculated as the mean of Cumulative Abnormal Returns in a [-1,1] window around RepRisk incidents between two closest price target changes for the same analyst. The controls include *TobinQ*, *Logarithm of Market Cap*, and *Time to Previous Price Target Change* (*Days*).

Table 9: Estimates of Equation (8) with sum of CARs as one the independent variables)

	ΔPTG (1)	ΔPTG (2)	ΔPTG (3)
Material ESG Incidents	-0.00237**		-0.00224*
	(-2.662)		(-2.514)
Not Material ESG Incidents		-0.00406**	-0.00434***
		(-3.181)	(-3.378)
SASB Treatment	-0.01908***	-0.02065***	-0.02082***
	(-11.531)	(-12.569)	(-12.261)
Material ESG Incidents × *SASB Treatment*	0.00086		0.00043
	(0.906)		(0.452)
Not Material ESG Incidents × *SASB Treatment*		0.00654***	0.00668***
		(4.520)	(4.591)
Sum of CARs	0.27390***	0.27492***	0.27404***
	(44.769)	(44.995)	(44.794)
Observations	205,225	205,225	205,225
Adjusted R^2	0.06248	0.06253	0.06256
Controls	Yes	Yes	Yes
Fixed Effects	Firm & Year	Firm & Year	Firm & Year

Note: Coefficients are followed by t-values in parentheses. '***', '**', and '*' indicate significance at levels of 0.01, 0.05, and 0.1, respectively.
OLS regression for equation 18. The dependent variable is the percentage change in price target forecasts on the analyst level, which is calculated for two closest price target changes for the same analyst as the difference between the price after and the price before divided by the price before. *Material/Not Material ESG Incidents* are calculated using RepRisk data. The materiality of ESG incidents is defined based on the SASB materiality finder. *Sum of CARs* is calculated as the sum of Cumulative Abnormal Returns in a [-1,1] window around RepRisk incidents between two closest price target changes for the same analyst. The controls include *TobinQ*, *Logarithm of Market Cap*, and *Time to Previous Price Target Change* (*Days*).

5 Conclusion

This paper examines the impact of SASB materiality standards on analyst price targets following ESG incidents.

The results of the event study performed though the Fama & French Plus Momentum model demonstrate that ESG incidents are associated with negative market reaction and more severe incidents cause lower CARs on the day after the event. These findings indicate that market participants on average value ESG, which is reflected in negative CARs following the negative ESG news and is in line with the recent literature on market reactions to ESG events.

In line with the prior research, the findings show that analysts react to negative ESG events through the changes in recommended prices forecasts. Going beyond the existing studies, the negative reaction of analysts is revealed for the price target changes for the same analyst using the staggered release of the SASB materiality classifications between 2013 and 2016 as shocks to sustainability disclosure. It is revealed that both material and not material ESG incidents are associated with negative and significant analyst responses, yet there is a positive shift in analysts' reaction to not material ESG incidents after the introduction of SASB standards. The inclusion of the mean and the sum of Cumulative Abnormal Returns, representing the market reaction, helps to indicate the reaction of financial analysts, which is not captured by the market reaction. The paper suggests that when accounting standards emphasize topics intended to benefit investors, they can create an important downside by eliminating the negative reaction of financial analysts to not material ESG incidents in their price targets forecasts.

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