Public perception, identification, and market impact of ESG events

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Abstract

We propose a novel procedure for detecting ESG-specific 'events' using a large dataset of news and social media. Tracking firm-specific sentiment and controversies, we find a significant impact of both positive and negative ESG events on stock market valuations, with larger reactions observed for negative events. Surprisingly, when classifying events as either E, S, or G, the observed price impact is mainly concentrated in the Social and Governance pillars, with little reaction to Environmental issues. Significant heterogeneity is observed when decomposing the results across industries, revealing strong responses in the Technology, Basic Materials, and Consumer Cyclicals sectors, but little evidence of an effect in the Financial and Industrials sectors. Finally, we provide evidence that the impact of media ESG events has declined over time, but only for negative events, suggesting a changing valuation of ESG risks.

1 Introduction

Concerns over social and environmental challenges are on the rise, prompting greater pressure on companies to address them. In a recent survey (Morgan Stanley, 2024), over 77% of individual investors expressed a desire to invest in companies with sustainable practices, and around 54% were planning to boost their investments in sustainability in the next year. Over the last decade, ESG investing has significantly gained traction among investors, and despite debates, inflows into sustainable funds remain strong (Institute for Energy Economics and Financial Analysis, 2024). The growing importance and profound impact of sustainable investments emphasize their crucial role in shaping the contemporary investment landscape.

Despite its rapid growth in market share, however, sustainable investing is still a relatively recent phenomenon with no commonly agreed standards in place. Sustainability performance, typically evaluated through Environmental, Social, and Governance (ESG) pillars, relies on a wide range of metrics and reporting frameworks,

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which vary across countries, and change over time. Many of these frameworks are also voluntary, granting companies flexibility in what they disclose (Berg et al., 2019). Hence, in order to evaluate how effectively a company is managing its ESG risks, diverse information sources are needed to provide a clear picture of ESG performance.

To this end, traditional ESG ratings (hereafter, TradESG ratings) aim to offer investors quantitative measures of companies' ESG performance (similar to credit ratings used to assess companies' creditworthiness). These ratings are constructed from heterogeneous sources of disclosure data (such as annual reports, CSR reports, company websites, etc.). These measures are presented in the form of numerous provider-specific ratings; each corresponding to a distinct ESG-related topic, such as "Carbon Emission", "Diversity Efforts", etc.[1]

The TradESG ratings have been thoroughly explored in the extant literature, with a large focus on investigating the relation between ESG performance and various factors including market structure, board structure, executive compensation, ownership characteristics, firm value, to name a few (see Gillan et al., 2021, for a review). However, subjectivity and variability among raters have led to extensive criticism of TradESG ratings (see, for example, Avramov et al., 2022; Berg et al., 2019; Chatterji et al., 2016; Li and Polychronopoulos, 2020; Serafeim and Yoon, 2022b). Chatterji et al. (2016) were the first to point out the divergence in scores among raters arising from variations in what raters choose to measure and how consistently those issues are measured; making conclusions based on these ratings potentially biased. Taking a step further, Berg et al. (2019) discovered that the significant divergence among TradESG data providers is primarily explained by differences in measurement, followed by limited coverage and the choice of weighting scheme.

The infrequent issuance and delayed timing of TradESG ratings also pose significant limitations. This arises from the extensive process involved in generating ratings, where rating agencies typically employ ESG analysts to gather and assess data from diverse sources. As a result, ESG ratings are generally available on an annual basis. While raters may reassess ratings earlier in the event of a major sustainability incident, such occurrences are relatively rare (Christensen et al., 2022).

Motivated by these shortcomings, we turn our attention to non-traditional ESG data derived from media sources in an attempt to assess the more immediate impact of ESG-related events on firm values. Alternative data providers offer a unique "outside-in" perspective by leveraging external sources, such as news and social media, to evaluate ESG impacts independently of company disclosures. This approach provides a real-time, dynamic view of ESG performance, utilizing advanced AI and NLP techniques to extract relevant information from unstructured data. We apply these data to identify ESG events and analyze their effects on asset prices using a standard event study approach. The event study methodology, widely adopted and recognized in the literature, offers the flexibility needed to fit our specific research purpose. Additionally, the data vendor's uniform approach to sentiment extraction from a broad range of news and social media platforms ensures data availability and consistency, eliminating the need for customization or tweaking of NLP algorithms. This uniformity enhances compatibility and contributes to the broader discourse. Consequently, this allows us to focus on contrasting the sensitivities of firms and industries to major ESG events and examining how information propagates through financial markets in

[1] See MSCI ESG Ratings Methodology (2024) and Environmental, Social and Governance (ESG) scores from LSEG (formerly, Refinitiv) (2023).

response to these events.

Text as data has proven to be a powerful predictor (Gentzkow et al., 2019). The signal aggregated from non-ESG-specific news articles, blogs, forums, and tweets, has been demonstrated to contain information that is not present in standard numerical financial or accounting data (Gu and Kurov, 2020; Fraiberger et al., 2021). Therefore, the focus on ESG-specific news seems a natural extension (see Capelle-Blancard and Petit, 2019, for an early example). Indeed, over the last two decades, information technology has revolutionized news dissemination, leading to widespread coverage of multinational companies' actions and behaviors, including daily ESG-related news flooding the media (BusinessWire, 2022; Eco-Business, 2022). As a result, ESG news can hold significant power in shaping investor perceptions and can profoundly impact companies' reputation and market performance. For example, on November 2, 2014, the fashion manufacturer Monclear was accused in an Italian news magazine of mistreating geese during the harvesting process. This scandal triggered a surge in negative comments on social media, ultimately causing a 5% decrease in market value, even though Monclear had denied the allegations (Gistri et al., 2018).

Acknowledging the potential importance of social media on stock valuations, our analysis uses data from both ESG-related news articles and social media posts to offer a comprehensive perspective on firms' sustainable performance. On the one hand, conventional news facilitates the transmission of new information, triggering market reactions, mitigating information asymmetry, enhancing trading activity, and drawing investor attention (Serafeim and Yoon, 2022a). On the other hand, posts on social media provide insights into fundamentals in environments with low analyst coverage and limited information from regular news media (Bartov et al., 2018; Gu and Kurov, 2020). The inclusion of social media in our analysis is perhaps even more relevant given the increasing importance of social media relative to conventional news in more recent years (see, for example, Gan et al., 2020).

Investigation of market reactions to ESG-specific media events (hereafter, MediaESG events) has only just started to emerge, with notable studies including Capelle-Blancard and Petit (2019), Serafeim and Yoon (2022a) and Lohre et al. (2023). In our paper, we contribute to this growing literature by providing a novel and flexible procedure for the identification of such MediaESG events. To date, there appears to be three distinct approaches used in the literature to identify these events. The first is to simply use a predefined list of MediaESG events provided by third-party vendors, such as Covalence EthicalQuory (Capelle-Blancard and Petit, 2019) or RepRisk (Orpiszewski et al., 2023; Sun et al., 2022). These ready-to-use lists are extremely easy to use, however they do not provide much flexibility as the event detection is dependent on the proprietary methodology employed by the data provider. Moreover, these predefined events are typically sourced only from news articles, focus predominantly on negative events, and often lack differentiation in the severity of the reported incidents.

The second approach, at the other extreme, is to extract the events from the raw textual data itself using dictionary-based or more sophisticated algorithmic approaches. For example, Flammer (2013) filters news articles using a list of ESG-related keywords and manually classifies them as either eco-friendly or eco-harmful, and Lohre et al. (2023) trains a deep-learning language model to classify news as controversial based on manually annotated samples. While these methods offer greater control over defining a MediaESG event, they often result in a comparably low number of extracted events or require fitting numerous hyperparameters that may drastically impact the resulting set of events. Moreover, the heterogeneity in training samples and the ad hoc approach to labeling these textual data by individual research teams further hinder the comparability and reproducibility of these studies, making adoption and implementation challenging.

To mitigate these shortcomings, the third approach, adopted in this paper, is to extract MediaESG events from commercially available standardized MediaESG sentiment scores. Examples of this approach include the use of daily changes in the Pulse score provided by TruValue Labs (see Serafeim and Yoon, 2022a; Tanaka and Managi, 2023), the change in the negative sentiment score provided by RavenPack (Cui and Docherty, 2020), and a change in the rating score provided by RepRisk (Wong and Zhang, 2024). This third approach serves as a middle ground between the other two approaches, offering greater flexibility in defining MediaESG events without the need for manual annotation or the use of 'black box' models, with little insight into why such events have been identified. For these reasons, we take this third approach in our paper and propose a straightforward and easy-to-implement event-detection algorithm to extract MediaESG events from the relatively unexplored Refinitiv ESG MarketPsych dataset.

We then perform a classical event-study analysis on the stock-price reaction of the S&P 500 constituents over a 22-year period using the MediaESG events identified from our detection algorithm. We thus contribute to the divergent literature on quantifying the stock price reaction of MediaESG events, which has shown conflicting results dependant on the sample period and event-detection approach used. Specifically, some studies only observe a positive and significant effect of ESG-friendly events (Serafeim and Yoon, 2022a), others emphasize that only negative ESG news results in a significant decline in market value (Capelle-Blancard and Petit, 2019), while several state that the significant effect occurs in both directions, aligning with the polarity of the news (Flammer, 2013; Tanaka and Managi, 2023). We find that companies significantly react to both positive and negative MediaESG events, with the direction of the effect aligning with the polarity of the event. We also observe an asymmetry in the magnitude of the impact, where negative events receive a greater response from asset prices than positive ones. Specifically, we document monthly reactions of 37bps and 61bps to positive ESG and ESGControversies events, respectively, and −110bps and −95bps to negative events, respectively.

Our approach also allows us to investigate the stock price reaction to MediaESG events defined from different sustainability issues (for example, for E, S, and G, separately). We observe significant reactions to both positive and negative Social and Governance media events, with monthly CAR reactions of 26bps and −99bps for Social events, and 23bps and −85bps for Governance events in positive and negative cases, respectively. In contrast, for Environmental events, we find no significant results for positive events, and a significant negative reaction of −66bps to negative events. However, while we find a significant reaction to negative events over the entire event window, there is no notable drop in the abnormal return around the day of the event, unlike the response to the other two pillars.

Across industries and over time, we observed substantial heterogeneity in the impact of ESG and ESGControversies events. Consistent with the overall findings, certain industries, such as "Technology" and "Basic Materials", exhibit a significant and asymmetric response to these events. Additionally, our analysis indicates that industries generally react to Social and Governance pillar events, while showing little significance in response to Environmental pillar events across most sectors. Our period decomposition reveals that the impact of positive events remains stable or increases, whereas there is a dramatic decrease in the effect of negative events across all datasets in the post-2012 period.

In sum, this paper contributes to the literature in several key ways. Firstly, we use the Refinitiv ESG MarketPsych dataset (RM-ESG), a newly available resource providing MediaESG scores across diverse sustainable topics. Secondly, we introduce a novel method for extracting events from multivariate sentiment data, relying on basic statistical properties and requiring just four hyper-parameters to be set. Thirdly, using an event study methodology, we demonstrate a significant link between both positive and negative MediaESG events and stock prices, highlighting the heterogeneity of effects across pillars, industries, and over time.

The rest of the paper is structured as follows: Section 2 outlines our sample and the data used for returns and sentiment measures. We then discuss our approach to identifying events from the multivariate sentiment time-series, formally define our proposed event-detection algorithm, and provide a review of identified events, as well as an example of the methodology in Section 3. Section 4 outlines the research methodology employed for the event-study framework and presents our findings. Finally, Section 5 concludes the paper, and more technical details and robustness tests can be found in the appendices.

2 Data and Sample

Our study spans a 22-year period, January 2001 to December 2022, and covers 796 firms, the historical constituents of the S&P 500 index. The recent MarketPsych ESG Analytics dataset by Refinitiv (RM-ESG) provides sentiment rankings on a wide range of ESG-related issues sourced from both news and social media.[2] We collect returns data from the Center for Research in Security Prices (CRSP) and pricing factors from Kenneth French's data library.

2.1 MediaESG sentiment data

We use the MarketPsych ESG Analytics dataset by Refinitiv to gather information about ESG-related media sentiment. The dataset employs a natural language processing system based on artificial intelligence to monitor sustainability-related news and social media posts at the company level. Because the sentiment is derived solely from external media sources and not from materials published by the companies themselves, the RM-ESG dataset could be seen as an indicator of the external perspective on a company's ESG activities.

The scores in the RM-ESG dataset are available in two packages. The **Advanced** package consists of sentiment scores providing minute-by-minute analysis of the media content on around 80+ ESG-related themes. The **Core** package, built upon the Advanced package, is designed to be directly comparable with TradESG scores by Refinitiv, encompassing 10 Category scores, three Pillar scores, an overall ESG score (a

[2] We note that in August 2023, Refinitiv was rebranded as LSEG, after the 2021 takeover of Refinitiv by the London Stock Exchange Group (LSEG). However, we retain reference to Refinitiv since this was the name when the research was first undertaken.

weighted aggregation of three pillars category scores), an ESGControversies score (an aggregation of all controversies in the Advanced feed), and an ESGCombined score, which integrate both the overall ESG and ESGControversies scores. Each of the Core scores represents a 365-day exponentially-weighted average (with a 90-day half-life) of a specific subset of Advanced scores, transformed into an intra-industry percentile ranking from 1 (worst in the industry) to 100 (best in the industry) rank.[3]

Our study focuses on the data sourced from the Core package, which addresses the sparsity issues present in the underlying Advanced package, adjusts for industry effects, and is more accessible and comprehensible for practitioners, given its similarity in design to the TradESG scores from Refinitiv. For the analysis, we use five core scores, including two aggregate scores (excluding ESGCombined, which is a combination of the other two) and three pillar scores.[4]

*** Insert Figure 1 about here ***

To illustrate our data, Figure 1 shows the temporal distribution of MediaESG and TradESG scores for Apple across several dimensions. TradESG scores are available on an annual basis, while MediaESG scores exhibit daily fluctuations, reflecting the dynamic nature of a company's media ESG image across time. This highlights the advantage of using frequent MediaESG scores as a more timely signal of a company's ESG performance.

A conceptually different metric within the dataset is the *Buzz*, which quantifies the volume of media references to, or chatter about, a particular company concerning ESG topics. MediaESG sentiment scores incorporate the buzz measure into their formulae for the normalization process—to account for the varying level of media attention about companies, making Buzz a vital measure to consider when identifying potentially material ESG events.

*** Insert Figure 2 about here ***

Figure 2 presents the distribution of MediaESG buzz over time and across sample companies. Figure 2a highlights that the volume of MediaESG buzz was nearly four times lower in the early 2000s, averaging around 5,000 ESG references, compared to the late 2022, where it surged to approximately 20,000 ESG references. This trend suggests

[3]More details can be found in the MarketPsych documentation.

[4]Note that we use both the aggregate ESG score and the ESGControversies scores in our analysis, since each metric offers a different perspective on ESG performance. Specifically, based on the official documentation, we identify at least three key differences between the two metrics. Firstly, ESGControversies focuses only on negative ESG performance, whereas the ESG score reflects the net balance between positive and negative impacts. This difference arises from the underlying design; for instance, in the case of CarbonEmission events, the ESG score would incorporate both positive and negative references, while ESGControversies includes only the negative ones. Secondly, not all sustainable topics are shared between ESG and ESGControversies scores. For example, while both scores include negative CarbonEmission impacts, the ESG score also evaluates a company's recycling efforts, whereas ESGControversies includes industrial accidents. Thirdly, ESG scores are computed as an average of sustainable category scores weighted by industry-specific materiality matrices, whereas ESGControversies aggregates controversies across all controversy categories as is. These differences indicate that, although closely related, ESG and ESGControversies scores likely contain different information.

increasing media attention towards ESG practices among the historical constituents of the S&P 500. Figure 2b illustrates how this buzz is distributed across our sample companies. As one would expect, companies like Meta (formerly Facebook) and Apple receive significant media attention regarding their ESG practices, while others like Trane Inc. and Alexandria Real Estate Equities Inc. garner less attention.

2.2 Other data

To analyse the short-term impact of MediaESG events on stock prices, we obtain stock return data from CRSP via Wharton Research Data Services over the entire period. We also collect the risk factors used in Fama and French (2016) from Kenneth French's data library for the same period.[5]

Finally, we compile a list of significant corporate events for each company in our sample using Refinitiv Eikon to avoid the confounding effect of multiple overlapping events. These events include earnings calls, earnings releases, annual meetings, M&A calls, stock splits, and more (see Appendix A for details).

2.3 Sample building

From January 1, 2000, to December 31, 2022, we identified 1,007 unique Refinitiv PermIDs corresponding to the historical constituents of the S&P 500 index (Refinitiv Identification Code, or RIC, #0.SPX) during the specified period. Among these, we successfully mapped CoreESG scores from the RM-ESG for 987 companies. Subsequently, we matched 910 of these companies to the corresponding pricing data from CRSP.

*** Insert Figure 3 about here ***

Figure 3a displays the distribution of non-missing months where both CoreESG scores and CRSP pricing data are available for each company. While around 400 companies have data from both sources for all the months used in the study, some companies only have data available for a few months. To ensure an adequate history of data for the event identification algorithm and event study settings, we require a minimum of five years (60 months) of data for inclusion in the analysis. This filtering process results in a sample size of 796 companies. Additionally, Figure 3b depicts the data availability in terms of the number of companies distributed over time. Although there is a slight imbalance in data availability, with a peak in 2005, our empirical strategy focuses on an event study rather than panel data analysis, thus minimizing the impact of this imbalance on our study's validity.

3 Event Identification

We define a MediaESG event as the sudden and notable emergence of new information that carries a distinctly positive or negative sentiment. This categorization ensures the

[5] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

exclusion of events that are ambiguous (e.g., a policy change that has both supporters and detractors within the media) or that fail to catch the media's eye (e.g., a sustainability initiative that does not lead to an uptick in media references).

For example, a negative MediaESG event might be a major environmental disaster, such as a large-scale industrial oil spill that results in extensive damage to ecosystems and generates widespread negative press. Another example could be a significant corporate governance failure, like a high-profile case of executive fraud that shakes investor confidence and attracts negative media scrutiny. Conversely, a positive MediaESG event could include the launch of a groundbreaking renewable energy project by a corporation, which receives acclaim for its innovative approach to reducing carbon emissions. Alternatively, a positive event could be a company's announcement of achieving gender parity across all levels of management, celebrated in the media for its commitment to diversity and inclusion.

We argue that events with the potential to sway company valuation can be characterized by four specific criteria, each related to the extent of media coverage and overall sentiment tonality.

Firstly, there must be an unexpected surge in the number of media references on the day of the event. Since companies vary in size and media coverage, the degree of this "surprise" should be assessed on a company-specific basis, rather than applying a uniform standard across all companies. For instance, an ESG-related event involving a large company like Apple is likely to be extensively covered by major media outlets, resulting in a significant absolute increase in references to the company. Conversely, a similar event for a smaller company may only garner attention from a handful of providers, leading to a relatively minor absolute increase in references; but both events could be equally as important for each company.

Secondly, there must be a sufficient level of media references on the day of the event. Since not all companies consistently attract media attention regarding their ESG practices, the surge captured by the first criteria could be caused by minor fluctuations in the absolute levels. Consider an extreme example where a company has no ESG topic coverage for an extended period. In such a case, a single mention could trigger a 'significant' event relative to the prior period. These are the types of instances we aim to avoid.

Thirdly, there should be an unexpected change in the media image of the company on the day of the event. Similar to the first condition, we aim to avoid capturing events that are part of a gradual trend. For instance, an increase in positive media coverage for a company already trending positively in overall sustainability ranking would likely have less impact than for a company with stagnant performance.

Fourthly, the event must represent the initial dissemination of information on the issue and not merely an update over subsequent days. For instance, consider a significant scandal involving a company's misuse of child labor. The emergence of such a case would impact the company's media perception regarding its social pillar performance, potentially resulting in an increase in references. However, as new information unfolds, subsequent shocks may be detected over the following days. While those subsequent events could still be interesting for further exploration, they are influenced by the initial dissemination of information. Therefore, their impact on stock prices may depend on the effect of the first event in the series. To ensure clarity, we exclude such events.

Given the above conditions, let us define a MediaESG event within the RM-ESG dataset context. To measure media coverage of a company, we will use the total number of ESG-related references captured by the Buzz measure. As for sentiment analysis, we will rely on the Core MediaESG ranks, which adjust for industry and offer insights into a company's sustainability impact and behavior across specific ESG topics. We can summarize the four conditions as follows:

Condition 1: *There is a sudden and pronounced increase in the company's Buzz on the day of the event.*

Condition 2: *There is a sufficient level of Buzz on the day of the event.*

Condition 3: *There is a sudden and pronounced change (either positive or negative) in the Core MediaESG score for the company on the day of the event.*

Condition 4: *There are no other events detected within a specified window preceding the event.*

It might be argued that, since the Core MediaESG ranks in Condition 3 indirectly incorporate the Buzz measure into its calculation (see Section 2), there should be no need for Condition 1 and Condition 2. We argue that, although there is a correlation between Buzz and MediaESG ranks in terms of levels, the variables do not usually move together in terms of their daily changes. To confirm this, we calculate the Spearman correlation coefficient for both the levels and daily changes between LogBuzz and MediaESG rank for each company in our sample, as shown in Figure 4.

*** Insert Figure 4 about here ***

As seen in Figure 4a, there is generally a positive correlation between Buzz and MediaESG rank, indicating that companies with higher media coverage tend to receive higher ESG ranks. This relationship could be attributed to Refinitiv's methodology of ranking the ESG scores, where buzz is used in the normalization process. However, Figure 4b shows a sufficiently lower correlation between the variables in terms of their daily changes. This suggests that a change in ESG rank typically doesn't coincide with a change in the Buzz measure. Hence, we contend that the Buzz measure offer a distinct perspective on MediaESG events compared to Core MediaESG ranks alone, and they should therefore be analyzed separately.

3.1 Multivariate event detection algorithm

Given the intuition behind the event detection conditions described above, we now provide a formal definition of our detection algorithm. For each company $i \in I$ and day $t \in T$, we define $x_{i,t} = \Delta X_{i,t} = X_{i,t} - X_{i,t-1}$ as a daily change in variable $X_{i,t}$ sourced from the CoreESG dataset. The variable could represent any of the ESG percentile-rank scores, such as *ESGControversies*, *SocialPillar*, as well as the *LogBuzz* metric.

To identify "events" within a time series, it is crucial to model the typical fluctuations in the variable over time. This modeling allows us to quantify the degree to which a new change deviates from the established pattern. For example, if variables A and

B typically fluctuate by 10 and 2 units, respectively, then a change of 5 units would not be considered abnormal for variable A, but it would be noteworthy for variable B.

The most straightforward way to capture historical fluctuations is to use the standard deviation of the changes, and so we define

$$\sigma_h(x_{i,t}) = \frac{1}{h}\sum_{z=1}^{h}(x_{i,t-z} - \overline{x}_{i,t}^h)^2, \text{ where } \overline{x}_{i,t}^h = \frac{1}{h}\sum_{z=1}^{h} x_{i,t-z}, \tag{1}$$

which corresponds to the standard deviation of the daily change in variable $X_{i,t}$ over the window of size h. Note that $\sigma_h(x_{i,t})$ does not include current time-period t in the calculation to control for the look-ahead bias.

Next, we define $\widetilde{x}_{i,t}^h = x_{i,t}/\sigma_h(x_{i,t})$, which normalizes the changes, measuring the severity of the change in $X_{i,t}$ on day t relative to its historical pattern over the past h days (excluding day t). Essentially, this can be interpreted as a *z-score* of the change. In this manner, it becomes convenient to classify the change $x_{i,t}$ as extreme based on the magnitude of $\widetilde{x}_{i,t}^h$. We define the hyperparameter k as the threshold of $|\widetilde{x}_{i,t}^h|$ used to define "extreme" changes, thus defining an extreme event as one that is k standard deviations away from its historical rolling mean.

For the Buzz measure, in addition to conditioning on the magnitude of $\widetilde{x}_{i,t}^h$, we also need to condition on the *level* of Buzz itself (Condition 2). Consider a company that receives infrequent media references regarding its ESG practices throughout the year, resulting in its buzz measure fluctuating with a standard deviation of 1. If the number of references increases by 3 units on a single day, it would be flagged as significant by Condition 1, however the event's economic significance would remain low. For these reasons, we define a hyper-parameter q as the minimum level of *LogBuzz* on the event date for it to be considered as valid.

Lastly, let us define $E_{i,t}$ as a MediaESG event on day t for company i and define the hyperparameter Z as the number of days in the look-back window to search for another events. This way, when defining the event we will require there to be no preceding events in the window of Z days.

Now, given hyperparameters k, h, q, and Z, and time-series $S_{i,t}$ and $B_{i,t}$ being daily *Core MediaESG score* and *LogBuzz*, respectively, we can write the four detection conditions mathematically as:

Condition 1: $\left|\widetilde{b}_{i,t}^h\right| \geq k$ (Buzz shock condition)

Condition 2: $B_{i,t} \geq q$ (Buzz level condition)

Condition 3: $\left|\widetilde{s}_{i,t}^h\right| \geq k$ (Score shock condition)

Condition 4: $\sum_{z=1}^{Z} E_{i,t-z} = 0$ (No re-occurrence condition)

For robustness, in Appendix B, we perform a sensitivity analysis of our results by varying the parameters k, q, h, and Z across a wide range of values.

3.2 Illustration using T-Mobile

In this section, we illustrate the proposed algorithm for event identification using a case study on T-Mobile spanning from January 2014 to January 2016. We employed a 90-day window ($h = 90$) to estimate the shock distribution, then selected shocks that were 3 standard deviations away from the mean ($k = 3$). Additionally, we required the level of buzz on the day of the event to exceed 10 references ($q = 10$) and ensured that there were no previously identified shocks in the time-series within 20 days before the event ($Z = 20$).

*** Insert Figure 5 about here ***

Figure 5 outlines the step-by-step pipeline of the proposed event identification algorithm. For illustration purposes, we use the ESGControversies score as the sentiment input variable and LogBuzz as a metric for media coverage.

In the upper panel of Figure 5, we display the original ESGControversies ($S_{i,t}$) and LogBuzz ($B_{i,t}$) metrics. Both measures demonstrate high volatility and appear to exhibit a negative correlation. Notable drops in the ESGControversies score are observed in July and December 2014, as well as in October 2015, dates which could potentially correspond to MediaESG events.

In the second graph in Figure 5, we illustrate the absolute daily changes in both the ESGControversies ($s_{i,t}$) and LogBuzz ($b_{i,t}$) metrics. Typically, the series fluctuate around zero as anticipated, although certain dates exhibit noticeable spikes in either one metric or both simultaneously.

The third plot in Figure 5 illustrates the standardized absolute daily changes for the ESGControversies ($\widetilde{s}^h_{i,t}$) and LogBuzz ($\widetilde{b}^h_{i,t}$). Notable spikes exceeding the designated threshold ($k = 3$) are denoted by circles and diamonds. While numerous local shocks are identified individually for each time series, only three instances (highlighted by vertical dashed lines) align between both metrics. These three dates, which also satisfy Condition 2 and Condition 4, are considered as MediaESG events for T-Mobile over the selected period of time.

To verify the algorithm's effectiveness, we manually assessed the identified dates by searching online news articles using the Google search engine. The results revealed significant events corresponding to the dates flagged by the algorithm. Specifically, on July 1st, 2014, T-Mobile faced accusations of applying bogus charges on customers without their consent, as reported by various news outlets such as USA Today, CNN, and CBS.[6] On December 19th, 2014, T-Mobile was fined by the US Government over the Cramming Case, according to reports from sources like FTC Government, Yahoo News, and Time.[7] Lastly, on October 1st, 2015, hackers stole personal data from 15 million individuals who had recently applied for T-Mobile's service, as reported by The Guardian, CNN, and Wired.[8]

[6] See https://www.usatoday.com/story/tech/2014/07/01/ftc-tmobile/11913151/, https://money.cnn.com/2014/07/01/technology/t-mobile-charges/index.html, and https://www.cbsnews.com/pittsburgh/news/regulators-accuse-t-mobile-of-bogus-billing/.

[7] See https://www.ftc.gov/news-events/news/press-releases/2014/12/t-mobile-pay-least-90-million-including-full-consumer-refunds-settle-ftc-mobile-cramming-case, https://sg.news.yahoo.com/u-settles-lawsuit-t-mobile-u-over-cramming-171747293–finance.html, and https://time.com/3642244/t-mobile-cramming/.

[8] See https://www.theguardian.com/business/2015/oct/01/experian-hack-t-mobile-credit-checks-personal-information, https://money.cnn.com/2015/10/01/technology/tmobile-experian-data-breach/, and https://www.wired.com/2015/10/hack-brief-hackers-steal-15m-t-mobile-customers-data-experian/.

*** Insert Figure 6 about here ***

The algorithm can also be visualized through the joint distribution of standardized daily changes in ESGControversies and LogBuzz, as shown in Figure 6. The crosses represent specific dates within the sample period. Positive events identified by the algorithm fall within the thick green square in the top right corner, designated as the 'Positive' zone, while negative events are located in the thick violet area at the bottom right, referred to as the 'Negative' zone. We use these names to avoid ambiguity, eschewing terms like "increase in controversy score". For clarity, only dates with non-empty changes in both are displayed. The lighter green and violet squares represent "mild" MediaESG areas, where shocks range between 1.96 and 3 standard deviations from the mean.

3.3 Description of Identified Events

The proposed event-identification algorithm involves setting four key hyperparameters. While we conduct an analysis of the robustness of our results to the specification of these hyperparameters in Appendix B, we establish the following benchmark settings for our baseline results:

1. History window (h) set to 90 days, defining events based on the previous quarter's data.

2. Change magnitude in terms of standard deviation (k) set to 3, identifying extreme events when both Buzz and MediaESG score changes exceed 3 standard deviations from the historical pattern.

3. Minimum buzz level set to the level of 10 references ($q = 10$).

4. No re-occurrence window (Z) of 20 days, ensuring that no other events occur within a 20-day window.

For our event study analysis, we post-filter the identified events by excluding those that coincide with major corporate activities within a 3-day window (i.e., the day before, the day of, and the day after the event). Specifically, we exclude events that align with financially focused corporate activities such as Earnings Calls and Sales Releases, while retaining events like Conferences that may pertain to ESG performance. A full list of the included and excluded events can be found in Appendix A.

*** Insert Table 1 about here ***

Table 1 presents descriptive statistics for identified events spanning 2000 to 2022. On average, companies tend to have more positive events (33.1 per company) than negative ones (24.4 per company), with frequencies ranging up to a maximum of 88 positive events and 52 negative events per company. SocialPillar events are the most frequent among the three pillors, followed by the GovernancePillar and then the EnvironmentalPillar.

*** Insert Figure 7 about here ***

Figure 7 displays the co-occurrence matrix of various identified MediaESG Events. To measure the degree of overlap, we rely on the Jaccard Index, a statistical measure that quantifies the similarity and diversity between sample sets.[9] Note that the calculations are presented in aggregate for the positive and negative subsets combined. We find that the intersection between the three pillars and an ESG score, represented as a weighted average of the three, ranges from 27.79% to 37.09%. This range roughly corresponds to one-third per pillar, which aligns with the concept that each pillar contributes proportionately to the overall ESG score when taken on average across different industries. Additionally, although not depicted in the figure, we find that approximately 6.2% of ESG events do not correspond with any pillar events. There is also some overlap among the pillars themselves, suggesting that events on the same date may appear across multiple pillars, with Jaccard Index ranging from 10.98% to 14.88% across all possible pairs. We explore these overlapping events in Section 4.5.

*** Insert Figure 8 about here ***

When considering the temporal distribution of the identified events, Figure 8a shows that events are predominantly identified during weekdays, although there are still some events occurring on weekends. To incorporate these weekend events into our event study analysis, we map them with pricing data available on the next trading date after the event. Figure 8b illustrates the distribution of events throughout the sample period. Interestingly, events are fairly continuously distributed, with the lowest number of events identified in the early 2000s, likely corresponding to the lower prevalence of ESG-related news during that time.

*** Insert Figure 9 about here ***

We continue by examining the events in the cross-section, plotting the distribution of events across companies in Figure 9a. The distribution appears to be fairly balanced, with most companies having between 20 and 80 events available, and a maximum of around 110 events for any given company.

We also demonstrate that the identified events are not concentrated within specific periods of a company's history by calculating the normalized Herfindahl Hirschman Index ($nHHI$) for each company. The original HHI assesses market concentration based on participants' market shares. In our case, for each company i, the identified events divide the company's total history T_i into P_i periods, using the identified event dates. We thus define the HHI for event concentration using:

$$HHI_i = \sum_{p=1}^{P_i} \left(\frac{T_{i,p}}{T_i} \right)^2, \tag{2}$$

[9]The Jaccard Index, or Jaccard similarity coefficient, is calculated as the size of the intersection divided by the size of the union of two sets of events. In simpler terms, it measures what fraction of the identified events in two different categories (like Environmental vs. Governance) are common to both categories relative to the total unique events in both categories.

where $T_{i,p}$ is the length of period p. To account for variations in the number of events across companies, we use the normalized HHI:

$$nHHI_i = \frac{(HHI_i - {}^1/_{P_i})}{1 - {}^1/_{P_i}} \tag{3}$$

whose value range between zero (for uniformly distributed events) and one (when all events occur on the same day). The distribution of $nHHI$ among the companies is illustrated in Figure 9b. The distribution is heavily skewed towards zero, indicating that identified events are not concentrated or clustered within specific periods of a company's history.

4 Event Study Methodology and Results

4.1 Methodology

To evaluate the price response to the identified set of MediaESG events, we employ an event study methodology. This involves estimating normal returns for each event using a chosen asset pricing model during the estimation window, then applying the model during the event window to estimate abnormal returns surrounding the event. Figure 10 outlines the general process of conducting the event study. Additionally, we introduce a gap between the estimation and event windows to better isolate the impact of MediaESG events and minimize potential issues such as information leakage or market anticipation of the event.

*** Insert Figure 10 about here ***

During the estimation period, expected returns $\widehat{R_{i,t}}$ for each company i on day t are obtained by regressing the observed returns $(R_{i,t})$ on the Fama and French (2016) five factors as follows:

$$R_{i,t} = \alpha_i + \beta_i(M_t - RF_t) + \gamma_i SMB_t + \theta_i HML_t + \delta_i CMA_t + \phi_i RMW_t + \epsilon_{i,t}, \tag{4}$$

where the coefficients $\beta_i, \gamma_i, \theta_i, \delta_i$, and ϕ_i capture the sensitivities of the stock returns to the respective factors: market excess return $(M_t - RF_t)$, size premium (Small minus Big, SMB_t), value premium (High minus Low, HML_t), investment style (Conservative Minus Aggressive, CMA_t), and profitability measure (Robust Minus Weak, RMW_t). These factors are sourced from Kenneth French's Data Library.

During the event window, abnormal returns are defined as the difference between observed daily returns $(R_{i,t})$ and the expected returns $(\widehat{R_{i,t}})$ predicted by the fitted model in Eq. (4), thereby isolating the effect of the event on the stock's performance:

$$AR_{i,t} = R_{i,t} - \widehat{R_{i,t}}$$

Cumulative abnormal returns (CAR) and cumulative average abnormal returns $(CAAR)$ are then calculated as:

$$CAR_i[\tau_1, \tau_2] = \sum_{t=\tau_1}^{\tau_2} AR_{i,t},$$

$$CAAR[\tau_1, \tau_2] = \frac{\sum_{i=1}^{N} CAR_i[\tau_1, \tau_2]}{N},$$

where N is the number of identified events, and τ_1 and τ_2 represent the start and end of the event window, respectively. Following Krüger (2015), we employ a 200-day estimation window, a 50-day gap window, and a 21-day event window.

To mitigate the potential impact of heightened volatility during events, we adopt a similar approach as Lohre et al. (2023) by computing the standard deviation and significance within the event window itself, thereby preventing any overestimation stemming from quieter periods. Significance testing of the cumulative abnormal return is conducted through t-statistics:

$$t = \frac{CAAR[\tau_1, \tau_2]}{\sigma\left(CAR_i[\tau_1, \tau_2]\right)}\sqrt{N},$$

where $\sigma(\cdot)$ represents the sample standard deviation of cumulative abnormal returns measured from day τ_1 to day τ_2 within the cross-section.

4.2 Main results

Employing the event-study methodology described above to examine the price reactions to the events identified in Section 3.3 we arrive at the results in Table 2. This table offers a comprehensive summary of the event-study outcomes, presenting mean Cumulative Abnormal Returns (CARs) across various subsets of events, identified by the aggregate ESG, ESGControversies scores, and by specific ESG pillars. Additionally, the table reports the number of events and the number of associated companies for each subset.

*** Insert Table 2 about here ***

Overall, our analysis reveals a notable and enduring impact of MediaESG events on asset prices, consistent with the polarity of the events. Positive events elicit a significant positive market response in terms of mean CAR[-10, 10], particularly those identified using ESG scores (0.37%), ESGControversies (0.61%), Social pillar (0.26%), and Governance pillar (0.23%) scores. Albeit expected direction in response to positive and negative events and the associated asymmetry in these responses, the events in the Environmental pillar show no statistical significance on any day on the event window. Moreover, no clear pre-event trends were observed, except for the ESGControversies subset, which showed slight significance one day before the event.

On the other hand, negative events exert a significant adverse impact on asset prices, with magnitudes notably higher than those observed for positive events. Events identified using ESG and ESGControversies scores lead to a reduction in mean CAR[-10, 10] of -1.10% and -0.95%, respectively. Across the pillars, the greatest impact is shown by the Social pillar (-0.99%), followed by Governance (-0.85%) and Environmental (-0.66%) events. Unlike positive events, negative events exhibit significant pre-event trends in ESG, ESGControversies, and SocialPillar subsets. Significant CARs are observed at the beginning of the events window for EnvironmentalPillar events, which dissipate closer to the event.

*** Insert Figures 11 and 12 about here ***

To visually assess the disparity in magnitude between positive and negative events, Figures 11 and 12 provide the mean CARs along with confidence bands throughout the event window for each individual MediaESG time series; the two aggregate measures are shown in Figure 11 and the three pillars are shown in Figure 12. Despite observing significant pre-event trends for certain MediaESG events such as negative ESGControversies events, the figures still emphasize a notable decline on the day of the events, persisting over time. On the other hand, while there is a significant negative reaction to negative EnvironmentalPillar events, it is challenging to discern a notable decline on the day of the event.

There could be several explanations for the appearance of significant pre-trends. One possibility is the occurrence of other events within the event window. Despite our efforts to account for major corporate events, the algorithm operates independently for each score and removes recurrent events based solely on the same score. For instance, if an issue arises in the Social pillar one day, followed by a negative Environmental pillar event the next day, the pricing impact of the Environmental pillar event might be influenced by the preceding Social pillar event. However, if this were the case, we would also expect to see a significant pre-trend for positive events, not just negative events, raising doubt about this explanation. Alternatively, there could be early dissemination of information about negative events, causing the market to anticipate negative headlines in the media. While challenging to confirm, this seems like a plausible explanation for the observed results.

4.3 Industry decomposition results

In this section, we explore how MediaESG events impact asset prices across different industries. Specifically, we map our sample of companies to Refinitiv Business Classification (TRBC) sectors. Figure 13 shows the distribution of our companies across different sectors, where we see that most companies belong to the "Technology", "Consumer Cyclicals", and "Industrials" sectors. To ensure robust analysis, we exclude the least populated sector, "Academic and educational services", which contains only one company, Adtalem Global Education Inc. (formerly, DeVry Inc.).

*** Insert Figure 13 about here ***

*** Insert Tables 3 and 4 about here ***

Tables 3 and 4 present the 21-day mean CAR estimates across various industrial sectors for positive and negative MediaESG events, respectively. Interestingly, some sectors show effects that diverge from the overall trends observed in Section 4.2. For instance, the "Real Estate" and "Utilities" sectors exhibit negative (albeit statistically insignificant) reactions to positive MediaESG events, while the "Consumer Cyclicals" sector demonstrates a positive response to negative environmental news, albeit with only minor statistical significance.

Additionally, the asymmetry in the magnitude of the effect observed for the full sample of companies remains when looking within each industry.

Specifically, across the aggregate ESG and ESGControversies subsets, we observe not only a difference in statistical significance, but also an asymmetry in the magnitude of the effect, with sectors reacting more strongly to negative events than to positive ones. For example, all industries with the exception for "Industrials" demonstrate a significant response to negative ESGControversies events, ranging from -0.55% to -1.50%, with the most pronounced effect observed in the "Basic Materials" industry. In contrast, only seven industries demonstrate significance for positive ESGControversies events, with the most substantial effect of 1.41% observed for the "Basic Materials" industry. For ESG events, eight industries show a significant response to negative events, whereas only three demonstrate significance for positive events. The "Basic Materials" industry exhibits the most pronounced effect, with -2.01% for negative ESG events and 0.97% for positive ESG events.

*** Insert Figure 14 about here ***

Since the CAR over the full 21-day window does not give the full picture of price reaction, we also plot in Figure 14, the mean CAR over the entire event window, for each industry. We do this only for ESGControversies since this is where we find our strongest results. The figure reveals significant heterogeneity across the industries. However, we can clearly see that for industries with a significant 21-day price reaction the majority of the impact was observed around the date of the event.

When analyzing industries' response to pillar events, sectors primarily react to negative Social and Governance pillar events. Six industries demonstrate significant reactions, ranging from -0.98% to -1.71%, for negative Social pillar events, with the "Technology" sector exhibiting the strongest response. In contrast, only two industries show significant reactions to positive Social pillar events, with the "Consumer Cyclicals" sector leading the list with a 1.13% effect. For negative Governance pillar events, a significant effect, ranging from -1.28% to -1.75%, is observed across four industries, with "Technology" showing the most pronounced effect. Additionally, only two industries, "Consumer Cyclicals" (1.13%) and "Basic Materials" (1.00%), demonstrate a significant reaction to positive Governance pillar events.

Consistent with the overall results from Section 4.2, industries generally do not significantly react to Environmental pillar events. Few exceptions involve the "Utilities", "Real Estate", and "Energy" industries, which show significant reactions to negative Environmental pillar events with magnitudes of-1.40%, -2.57%, and -1.41%, respectively. Only "Industrials" sector exhibits a significant and positive reaction of 0.68% CAR[-10, 10] to positive EnvironmentalPillar events.

4.4 Period decomposition results

Furthermore, we break down the overall effect of MediaESG events on cumulative abnormal returns described in Section 4.2 by dividing the entire period into pre- and post-subsets. There are various ways to partition the period - based on specific sustainable macro events like the year of the Paris Agreement, or structural changes in the RM-ESG dataset such as the inclusion of Tweets data in 2010. However, given our analysis spans all three pillars and relies on both news and social media data, finding a single date applicable to all scores or separate dates for each score is challenging. Therefore, we choose to divide the dataset chronologically into two halves: from 2000 to 2011 and from 2012 to 2022. This division ensures a balanced number of events in each subset, facilitating a robust comparison of the pooled effects across the periods.

*** Insert Table 5 about here ***

Table 5 presents the number of events and the estimated mean CAR across the entire 21-day event window for each period and MediaESG score. Notably, the market demonstrates a significant response to general ESG and ESGControversies events across both subperiods. Specifically, positive events exhibit a consistent effect, with ESG events showing a slight increase from 0.28% to 0.47%, and ESGControversies events experiencing a stable effect from 0.60% to 0.62%. Conversely, the impact of negative ESG and ESGControversies events diminishes notably from the earlier to the later period. Post-2012, negative ESG events are associated with nearly two times lower mean-CAR reactions, plummeting from -1.48% to -0.70%, while negative ESGControversies events witness a decline in mean CAR from -1.12% to -0.77%.

For the positive pillar events, there is a significant and positive reaction to Social and Governance events in the post-period, with mean CAR responses of 0.30% and 0.50%, respectively. However, there is no significant reaction to positive Environmental pillar events in either of the periods, while the magnitude is rising to 0.22% in post-2012 period.

For the negative pillar events, however, there is a notable shift in the narrative. Each pillar exhibits a significant decline in the estimated effect from the earlier to the later period. Specifically, the Social pillar decreases from -1.22% to -0.75%, the Governance Pillar from -1.01% to -0.69%, and the Environmental Pillar from -1.03% to -0.37%. These effects hold significance for both periods and all pillars, except for the Environmental Pillar in the latest period.

4.5 Pillar overlap decomposition

In Section 3.3, we highlighted that events identified for each pillar separately may coincide on the same day with events from another pillar. While the overlap between two pillars is relatively small, it could still have a material impact on the observed stock price reaction.

We note that in cases of pillar overlap, a single event could be related to multiple pillars, resulting in its detection across multiple dimensions. Conversely, multiple events could also occur on a given day, each associated with different pillars. While we cannot distinguish between these two possibilities, it seems likely that the majority of the situations correspond to the former, given that, on average, only one event is detected per company per year (see Table 1). Additionally, the impact of having pillar events of different polarities on the same day remains unclear.

To investigate the overlap of pillar events further, we examine the stock price reaction to subsets of events covering all possible combinations of individual pillar events, including their polarity. The results are reported in Table 6.

*** Insert Table 6 about here ***

For each combination we provide an estimated CARs over the entire 21-day window, as well as the number of events associated with it. Panel A shows the 'raw' or 'pure' effect of each pillar event with no co-occurrence of other pillar events being observed on the same day. Although slightly lower in magnitude, the results for Social and Governance pillar events generally align with the main findings described in Section 4.2. Over the entire event window, the Social pillar exhibits a significant reaction to both positive (0.25%) and negative (−0.80%) events, while only negative Governance pillar events show a significant impact of −0.75% CAR. As for the 'pure' EnvironmentalPillar events, the results show greater magnitude and significance, with positive and negative events achieving CARs of 0.30% and −0.93% over a 21-day window, respectively.

In Figure 15 we depict the pure pillar effects across the entire event window. We observe that while pure positive EnvironmentalPillar events show some increased significance (at the 10% confidence level), there is little evidence of immediate changes on the day of the event, aligning closely with the aggregate results discussed in Section 4.2.

Panel B presents all the cases when two pillar events with similar or different polarity appear on the same day. We find that the overall effect is mainly insignificant with only a few exceptions. Firstly, when a positive EnvironmentalPillar event coincides with a negative SocialPillar event, we see a negative CAR reaction of −1.68% over 21-day window, which is higher than the mean reaction to either of the events separately. Secondly, we also find a significant negative CAR reaction when a negative SocialPillar event coincides with either positive (−1.05%) or negative (−1.66%) Governance events.

Panel C reports the results when all three pillars have identified events on a given day. We find that on the dates when both positive SocialPillar and GovernancePillar events coincide with either positive or negative EnvironmentalPillar event, there is a positive significant CAR[-10, 10] reactions of 1.72% and 3.08%, respectively. However, when negative EnvironmentalPillar and GovernancePillar events coincide with a positive SocialPillar event, we find a significant negative CAR[-10, 10] reaction of −3.28%.

In summary, when no co-occurrence between pillars is observed, the 'pure' effect of each pillar event aligns with the 'non-pure' baseline results from Section 4.2 in both magnitude and significance. The only notable difference is observed for 'pure' EnvironmentalPillar events, where we see increased magnitude and significance for both positive and negative subsets. However, upon detailed inspection of the time series of cumulative abnormal returns over the event window, there remains no clear impact on the day of the event itself, consistent with our baseline findings.

In cases of co-occurrences, the effect appears significantly influenced by the polarity of the SocialPillar event. Among the 16 possible combinations where a pillar coincides with any two others (excluding 'pure' events), Social Pillar events align in polarity with 13 of them, whereas Governance and Environmental Pillar events align with 11 and 6, respectively.

Overall, these results offer fresh insights into the intricate mechanisms governing pillar events.

5 Conclusion

In this study, we analyzed the reaction of asset prices to the appearance of new information in the form of ESG news and social media posts, denoted by the MediaESG events. Rather than relying on pre-defined lists of MediaESG events or building custom complex NLP models for text analysis, we take the novel multivariate approach for extracting the events from the processed series of media sentiment. The beauty of the approach is that it is based on simple statistical rules and requires as little as four hyperparameters to be set.

Using the custom approach, we extracted thousands of company-specific events across different sentiment series available in the recently developed yet not extensively used ESG-MarketPsych dataset by Refinitiv (RM-ESG). We obtain positive and negative subsets of events across various scores, including general ESG and ESGControversies scores, as well as per Environmental/Social/Governance pillars.

For each subset of events, we estimated a price reaction in the form of cumulative abnormal returns on the 21-days event window for the period from 2000 to 2022. We find a generally significant reaction to both positive and negative MediaESG events, that coincide in sign with the polarity of an underlying events. We, however, haven't noticed a significant reaction to positive Environmental Pillar events.

For the pillars, we also decomposed the overall aggregate effect into subsets based on the co-occurrence with other pillars or the same or different polarities on the same day. We find that the 'pure' effect for Social and Governance pillars roughly coincides with the one found in the main findings, while the magnitude of 'pure' Environmental pillar effect is greater. In the case of co-occurrence, we find the joint effect to be heavily dominated by the polarity of the SocialPillar event appearing on the day of the event.

Our industry decomposition revealed a heterogeneous effect of MediaESG events on asset prices across ten industry sectors. We found that all industries except for "Industrials" negatively react to negative ESGControversies events, with effects ranging from -0.55% to -1.50% mean CAR[-10, 10], while only seven of them demonstrate a positive and significant reaction to positive ESGControversies events. The effects observed for both positive and negative ESG events are less pronounced. Additionally, we explored the effects through the lens of pillars and found that a limited number of industries significantly react to Social and Governance pillar events, with responses to Environmental events being even more sparse.

For the temporal decomposition, we divide the entire period into fairly balanced halves of roughly eleven years, resulting in two periods from 2000 to 2011, and from 2012 to 2022. The decomposition reveals that there is a generally significant effect of both positive and negative MediaESG events on asset pricing in both periods. We find that although significant, the effect of negative MediaESG events diminishes over time, and for negative Environmental Pillar events loses the significance in the later period altogether. For the positive subset, there is a slight change in the magnitude of the effect for aggregate ESG, ESGControverises scores and Social pillar score. We spotted no significance to Environmental pillar events in any period, while the Governance pillar gained a significant 0.50% mean CAR[-10, 10] effect in the later period of the analysis.

From a practical perspective, this paper provides a new simple and automated algorithm to extract positive and negative MediaESG events from the processed sentiment series that could be easily employed by asset managers to timely adjust their holdings in companies involved in any MediaESG events. The underlying sentiment series are coming from the Core RM-ESG dataset, which is designed in a similar fashion to the conventionally used Traditional ESG ratings, making the implementation and the interpretation of the results easier for the end-users.

The limitation of the paper and the prospects for future research involve the further decomposition of the effect into narrower categories, such as ChildLabor and Emissions, as well as dissecting the co-dependency between pillar events appearing at the same time. Additionally, an important step could be to decompose the overall buzz measure into the buzz coming straight from the Environmental/Social/Governance pillars, which would benefit the overall detection algorithm.

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Tables and Figures

	Overall		Per Company		
	# Events	# Companies	Mean	Median	Max
Positive events					
Total unique	24607	744	33.1	31.0	88.0
ESG	10457	740	14.1	12.0	49.0
EnvironmentalPillar	6712	711	9.0	8.0	45.0
SocialPillar	8493	735	11.4	9.0	49.0
GovernancePillar	7606	733	10.2	9.0	34.0
ESGControversies	12870	737	17.3	16.0	55.0
Negative events					
Total unique	18137	743	24.4	25.0	52.0
ESG	5819	731	7.8	7.5	26.0
EnvironmentalPillar	2855	663	3.8	3.0	19.0
SocialPillar	5866	720	7.9	7.0	28.0
GovernancePillar	4617	718	6.2	6.0	21.0
ESGControversies	10186	741	13.7	13.0	38.0

Table 1: **Descriptive statistics of the identified MediaESG events over the entire period.** The upper and lower panels show the distribution of identified events for each MediaESG score, along with the total number of unique events across all five subsets for positive and negative events, respectively. Each subset displays the overall number of identified events, the overall number of companies with those events, and the mean, median, and maximum number of events per company (over the 22-year period).

	Positive Events CAR					**Negative Events CAR**				
	Aggregate		**Pillars**			**Aggregate**		**Pillars**		
Event Date	ESG	ESGControversies	Environmental	Social	Governance	ESG	ESGControversies	Environmental	Social	Governance
-10	0.01%	-0.01%	-0.02%	-0.02%	-0.01%	-0.03%	-0.03%	-0.10% ***	-0.03%	0.03%
-9	-0.00%	-0.02%	-0.03%	-0.04%	-0.01%	-0.06%	-0.07% **	-0.13% **	-0.05%	0.01%
-8	-0.00%	-0.01%	-0.04%	-0.03%	-0.04%	-0.09% **	-0.11% ***	-0.23% ***	-0.08% *	-0.04%
-7	-0.01%	-0.01%	-0.05%	-0.04%	-0.07%	-0.11% **	-0.11% ***	-0.19% **	-0.09% *	-0.07%
-6	0.00%	-0.01%	-0.06%	-0.05%	-0.03%	-0.12% **	-0.13% ***	-0.21% *	-0.16% ***	-0.08%
-5	-0.04%	-0.02%	-0.08%	-0.06%	-0.05%	-0.12% *	-0.18% ***	-0.20% *	-0.24% ***	-0.10%
-4	0.00%	0.01%	-0.03%	-0.03%	-0.04%	-0.13% *	-0.18% ***	-0.15%	-0.23% ***	-0.05%
-3	-0.01%	0.00%	-0.02%	-0.05%	-0.04%	-0.17% **	-0.23% ***	-0.13%	-0.27% ***	-0.09%
-2	-0.02%	0.01%	0.01%	-0.07%	-0.05%	-0.20% **	-0.28% ***	-0.18%	-0.32% ***	-0.06%
-1	0.00%	0.10% *	-0.01%	-0.05%	-0.04%	-0.45% ***	-0.37% ***	-0.23%	-0.45% ***	-0.23%
0	0.29% ***	0.67% ***	0.13%	0.37% ***	0.18% *	-0.90% ***	-0.93% ***	-0.31%	-1.08% ***	-0.72% ***
1	0.31% ***	0.67% ***	0.09%	0.35% ***	0.20% *	-0.99% ***	-0.96% ***	-0.42% **	-1.09% ***	-0.74% ***
2	0.33% ***	0.68% ***	0.11%	0.34% ***	0.21% *	-0.96% ***	-0.92% ***	-0.49% **	-1.06% ***	-0.70% ***
3	0.35% ***	0.71% ***	0.14%	0.37% ***	0.24% **	-0.98% ***	-0.92% ***	-0.52% **	-1.01% ***	-0.75% ***
4	0.36% ***	0.71% ***	0.14%	0.35% ***	0.26% **	-1.01% ***	-0.94% ***	-0.48% **	-0.97% ***	-0.78% ***
5	0.38% ***	0.70% ***	0.12%	0.34% ***	0.29% ***	-1.07% ***	-0.91% ***	-0.49% **	-1.02% ***	-0.82% ***
6	0.37% ***	0.65% ***	0.11%	0.33% ***	0.26% **	-1.13% ***	-0.96% ***	-0.51% **	-1.02% ***	-0.84% ***
7	0.37% ***	0.64% ***	0.07%	0.32% ***	0.26% **	-1.11% ***	-0.94% ***	-0.48% **	-1.01% ***	-0.78% ***
8	0.38% ***	0.66% ***	0.08%	0.32% ***	0.27% **	-1.13% ***	-0.92% ***	-0.52% **	-1.00% ***	-0.82% ***
9	0.38% ***	0.64% ***	0.10%	0.27% ***	0.25% **	-1.15% ***	-0.96% ***	-0.64% ***	-1.02% ***	-0.85% ***
10	0.37% ***	0.61% ***	0.12%	0.26% **	0.23% *	-1.10% ***	-0.95% ***	-0.66% ***	-0.99% ***	-0.85% ***
# Events	10481	12892	6729	8514	7620	5851	10220	2867	5906	4642
# Companies	740	737	711	735	733	731	741	663	720	718

TABLE 2: **The Impact of MediaESG Events on Cumulative Abnormal Returns (CAR).** The upper panel displays the estimated Mean CAR for each date in the 21-day event window. The lower panel indicates the number of identified events and companies used in estimating the effect. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Positive Events	Aggregate ESG	ESGControversies	Pillars (E)	(S)	(G)
Panel A: Mean CAR [-10, 10]					
Consumer cyclicals	0.48%	1.33%***	0.12%	1.13%***	1.13%***
Industrials	0.54%**	0.67%***	0.68%**	0.04%	0.03%
Financials	0.39%	0.02%	0.06%	-0.28%	0.15%
Utilities	-0.10%	-0.45%**	-0.35%	0.30%	-0.50%
Real estate	-0.16%	-0.14%	-0.24%	0.18%	-0.19%
Technology	0.68%**	0.86%***	0.15%	0.38%	0.39%
Energy	0.49%	-0.02%	0.50%	-0.77%	-0.26%
Basic materials	0.97%***	1.41%***	0.22%	0.49%	1.00%**
Healthcare	-0.05%	1.15%***	-0.25%	0.59%*	-0.04%
Consumer non-cyclicals	0.04%	0.55%**	0.13%	0.28%	-0.36%
Panel B: Number of Events					
Consumer cyclicals	1291	1750	801	1054	1026
Industrials	1495	1745	998	1189	1060
Financials	1245	1574	726	1073	960
Utilities	816	975	807	495	439
Real estate	758	947	299	689	503
Technology	1668	1933	1087	1410	1281
Energy	736	914	525	576	509
Basic materials	645	818	468	482	422
Healthcare	1143	1373	575	1055	871
Consumer non-cyclicals	623	800	407	438	490

Table 3: **The Impact of Positive Events on Firm Value by Sector.** Panel A displays the estimated average CAR values across the 21-days event window, while Panel B lists the number of events identified and used in estimating the effect. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Negative Events	Aggregate ESG	Aggregate ESGControversies	Pillars (E)	Pillars (S)	Pillars (G)
PANEL A: MEAN CAR [-10, 10]					
Consumer cyclicals	-0.69%	-0.95%***	0.76%	-0.99%*	-0.43%
Industrials	-0.07%	-0.34%	-0.72%	-0.14%	-0.35%
Financials	-0.85%**	-0.55%**	-0.97%	-0.49%	-0.69%
Utilities	-1.15%*	-1.36%***	-1.40%**	-1.70%***	-1.28%*
Real estate	-1.54%**	-1.03%**	-2.57%**	-0.98%**	-1.47%**
Technology	-1.86%***	-1.27%***	-0.60%	-1.71%***	-1.75%***
Energy	-1.25%*	-1.25%**	-1.41%*	-1.05%	-0.23%
Basic materials	-2.01%***	-1.50%***	-1.24%	-0.62%	-0.72%
Healthcare	-1.24%***	-1.09%***	-0.34%	-1.28%***	-0.23%
Consumer non-cyclicals	-0.95%**	-0.85%***	-0.33%	-1.12%***	-1.36%***
PANEL B: NUMBER OF EVENTS					
Consumer cyclicals	855	1378	399	879	709
Industrials	775	1320	390	822	589
Financials	758	1433	279	818	622
Utilities	341	488	247	319	226
Real estate	301	479	76	335	204
Technology	924	1639	434	886	828
Energy	410	710	301	355	301
Basic materials	276	526	187	249	233
Healthcare	712	1383	297	747	556
Consumer non-cyclicals	449	762	238	436	330

TABLE 4: **The Impact of Negative Events on Firm Value by Sector.** Panel A displays the estimated average CAR values across the 21-days event window, while Panel B lists the number of events identified and used in estimating the effect. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Positive Events 2000-2011	Positive Events 2012-2022	Negative Events 2000-2011	Negative Events 2012-2022
Mean CAR [-10, 10]				
ESG	0.28%*	0.47%***	-1.48%***	-0.70%***
ESGControversies	0.60%***	0.62%***	-1.12%***	-0.77%***
EnvironmentalPillar	-0.02%	0.22%	-1.03%***	-0.37%
GovernancePillar	-0.07%	0.50%***	-1.01%***	-0.69%***
SocialPillar	0.22%	0.30%**	-1.22%***	-0.75%***
Number of Events				
ESG	5374	5107	3018	2833
ESGControversies	6321	6571	5354	4866
EnvironmentalPillar	2904	3825	1228	1639
GovernancePillar	3637	3983	2294	2348
SocialPillar	4598	3916	3028	2878

TABLE 5: **The Impact of MediaESG Events on CAR by period.** The upper panel displays the estimated Mean CAR across the 21-days event window, while the lower panel indicates the number of events identified and used in estimating the effect. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

			CAR[-10, 10]	# Events
Panel A: Single Pillar Events				
E↑			0.30%*	3891
E↓			-0.93%***	1702
	S↑		0.25%*	5115
	S↓		-0.80%***	4016
		G↑	0.21%	4484
		G↓	-0.75%***	2875
Panel B: Double Pillar Events				
E↑	S↑		-0.11%	991
E↑	S↓		-1.68%**	296
E↑		G↑	-0.00%	788
E↑		G↓	-0.02%	248
E↓	S↑		0.30%	235
E↓	S↓		-0.82%	319
E↓		G↑	0.51%	212
E↓		G↓	-0.92%	207
	S↑	G↑	0.32%	1262
	S↑	G↓	0.01%	403
	S↓	G↑	-1.05%*	386
	S↓	G↓	-1.66%***	690
Panel C: Triple Pillar Events				
E↑	S↑	G↑	1.72%***	335
E↑	S↑	G↓	-1.84%	78
E↑	S↓	G↑	-1.17%	56
E↑	S↓	G↓	-3.04%	46
E↓	S↑	G↑	3.08%***	64
E↓	S↑	G↓	-3.28%*	31
E↓	S↓	G↑	-1.24%	33
E↓	S↓	G↓	-1.17%	64

Table 6: **Market reaction to pillar event co-occurrence** The table provides the estimated Mean CAR across the 21-day event windows and number of events identified for different combinations of pillar events occurring on the same day. By green upward and red downward arrows we denote positive and negative events, respectively. Panel A displays the market reaction to uniquely identified events across pillars and polarities. Panel B shows the market reaction when there are two events of similar or different polarity appearing on the same day. Panel C describes the market reaction when all three pillar events, either of the same or different polarity, appear on the same day. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

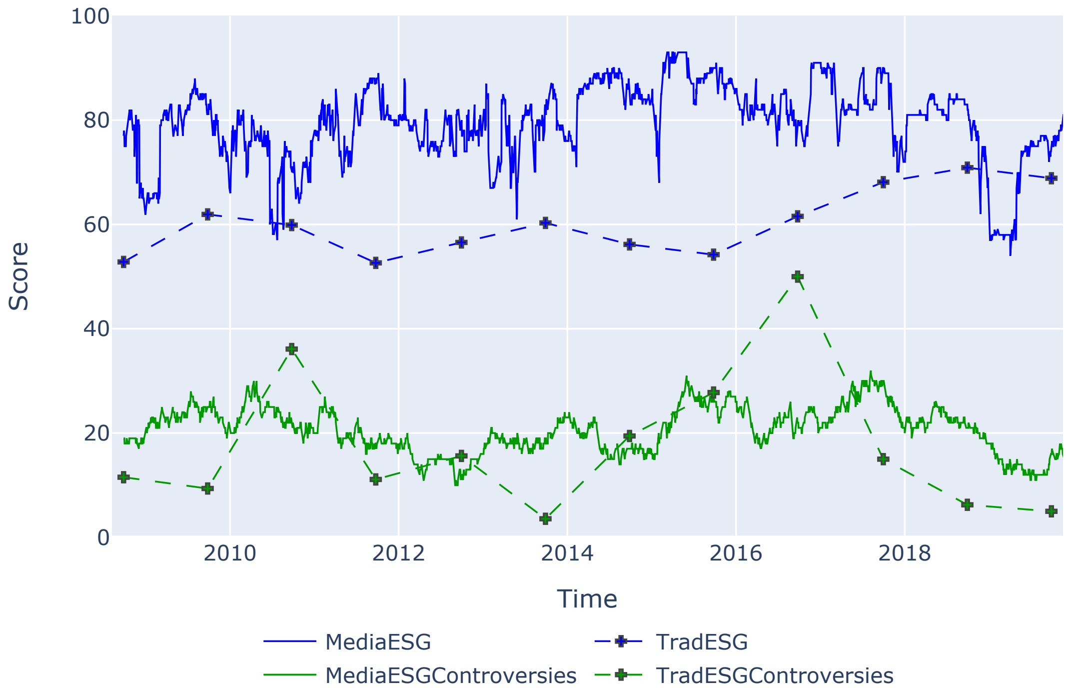
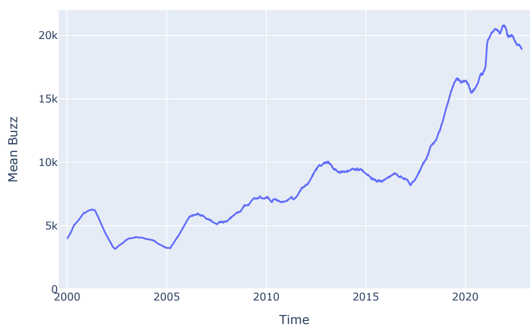
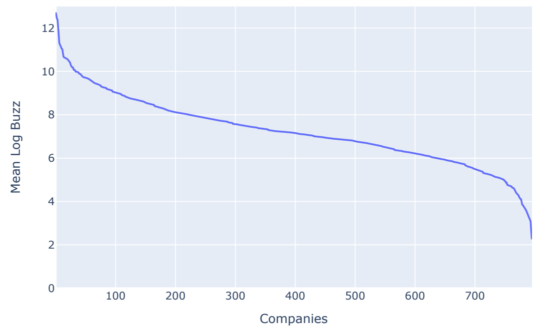


FIGURE 1: **MediaESG and TradESG scores for Apple from 2008 to 2020.** The MediaESG and MediaESGControversies scores, represented by solid green and blue lines, are sampled from the Refinitiv MarketPsych dataset. TradESG and TradESGControversies scores, depicted by dashed green and blue lines with crosses, represent the official ESG scores by Refinitiv, loaded from the Eikon application.

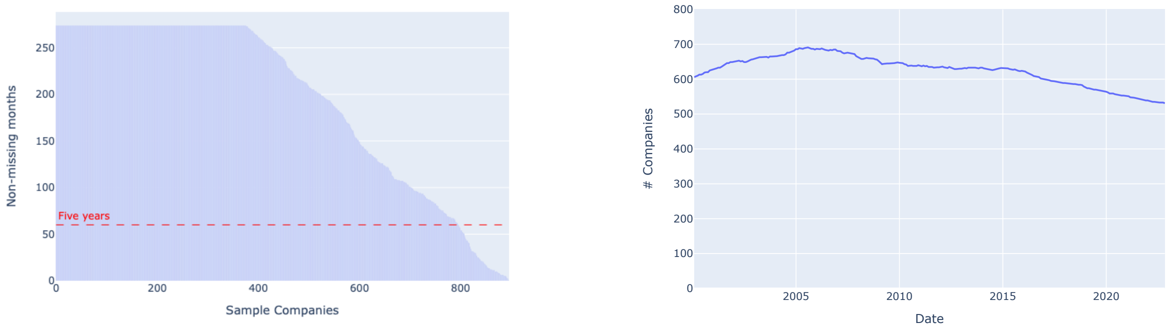


(A) Buzz over time



(B) LogBuzz in cross-section

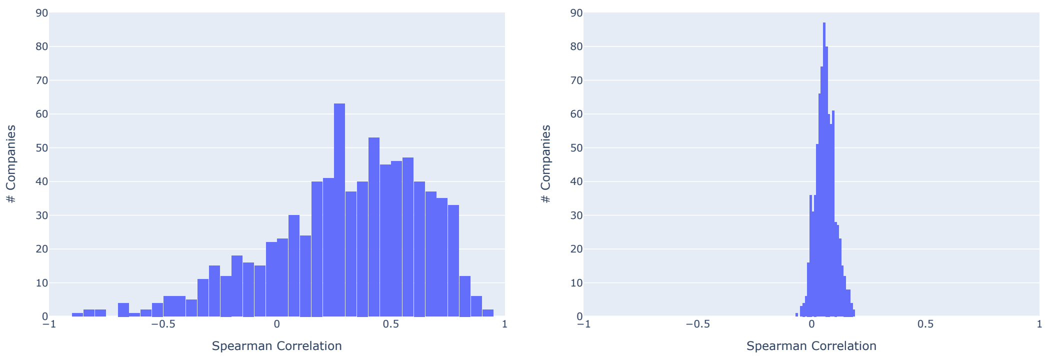
FIGURE 2: **Temporal and cross-sectional distribution of MediaESG Buzz.** The left plot illustrates the temporal distribution of mean buzz over the study period from January 2000 to December 2022. Each point represents the average buzz level calculated across sample companies for a specific date. The right plot shows the distribution of mean LogBuzz for each company over the entire sample period ranked from the highest to the lowest buzz. On the left-hand side of Panel B are the most salient companies, such as Apple, Facebook, Tesla, and on the right-hand side are the least salient, such as Trane Inc. and Alexandria Real Estate Equities Inc.



(A) Cross-section data availability

(B) Temporal data availability

FIGURE 3: **Sample Data Availability.** The left plot illustrates the number of months with both Core RM-ESG and CRSP data available for each company in the original sample. The dashed red line represents the threshold of 60 months used to filter out companies with insufficient data. The right plot displays the count of companies with non-missing observations available for each month of the sample period. Only companies with a total number of non-missing months exceeding 60 are included in the graph.



(A) LogBuzz vs. MediaESG score

(B) ΔLogBuzz vs. ΔMediaESG score

FIGURE 4: **Spearman Correlation between LogBuzz and Media ESG Rank.** Both plots illustrate the distribution of Spearman correlation coefficients across companies in the sample, with the left plot showing correlations in levels between LogBuzz and MediaESG rank, and the right plot displaying the distribution of the correlation in their daily change.

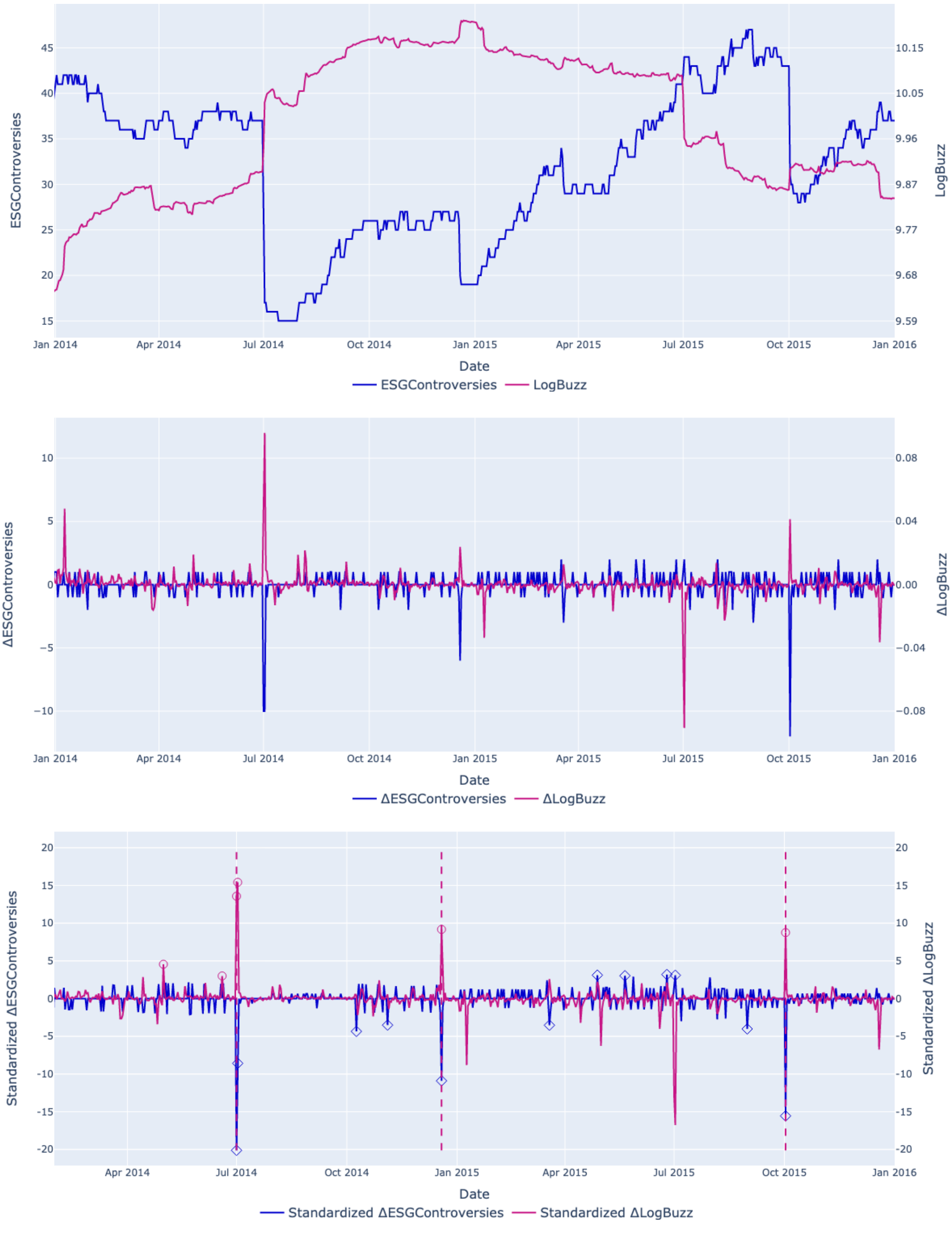


FIGURE 5: **Event Detection Pipeline example on T-Mobile from January 2014 to January 2016.** The top figure displays raw ESGControversies and LogBuzz data from the Core RM-ESG dataset. The middle figure shows the daily difference of the ESGControversies and LogBuzz variables. The bottom figure illustrates the standardized daily differences, calculated by dividing by the standard deviation of those differences over the previous 90 days (excluding the current date). Changes exceeding 3 standard deviations are marked as circles for LogBuzz and diamonds for ESGControversies. Vertical dashed lines indicate dates with notable increases in LogBuzz and significant changes (positive or negative) in ESGControversies.

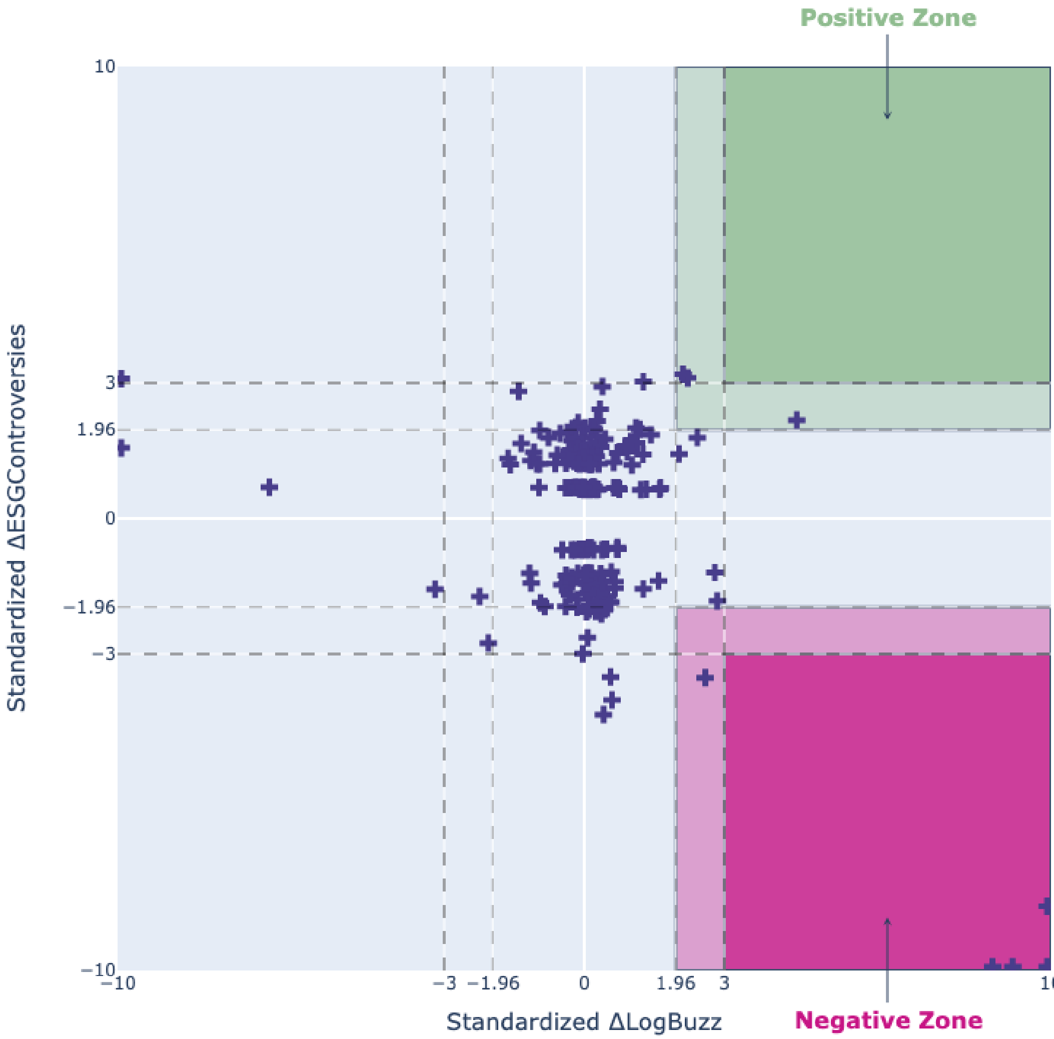


FIGURE 6: **Joint distribution of standardized ΔESGControversies and ΔLogBuzz.** The Δ differences are calculated on daily time-series and standardized by dividing by the standard deviation of those differences calculated over a 90-day history, excluding the actual date. Each cross represents a specific date for T-Mobile from June 2014 to January 2016. For representational purposes, dates where either LogBuzz or ESGControversies scores have not changed are excluded from the figure. The green 'Positive' zone captures dates with a notable increase in both ΔESGControversies and ΔLogBuzz, interpreted as positive identified events. The purple 'Negative' zone involves dates with a notable decrease in ΔESGControversies and a notable increase in ΔLogBuzz, interpreted as negative identified events in our analysis. Both positive and negative zones include thick-colored and blurry-colored areas, corresponding to increases of over 3 and 1.96 standard deviations away from the historical pattern, respectively.

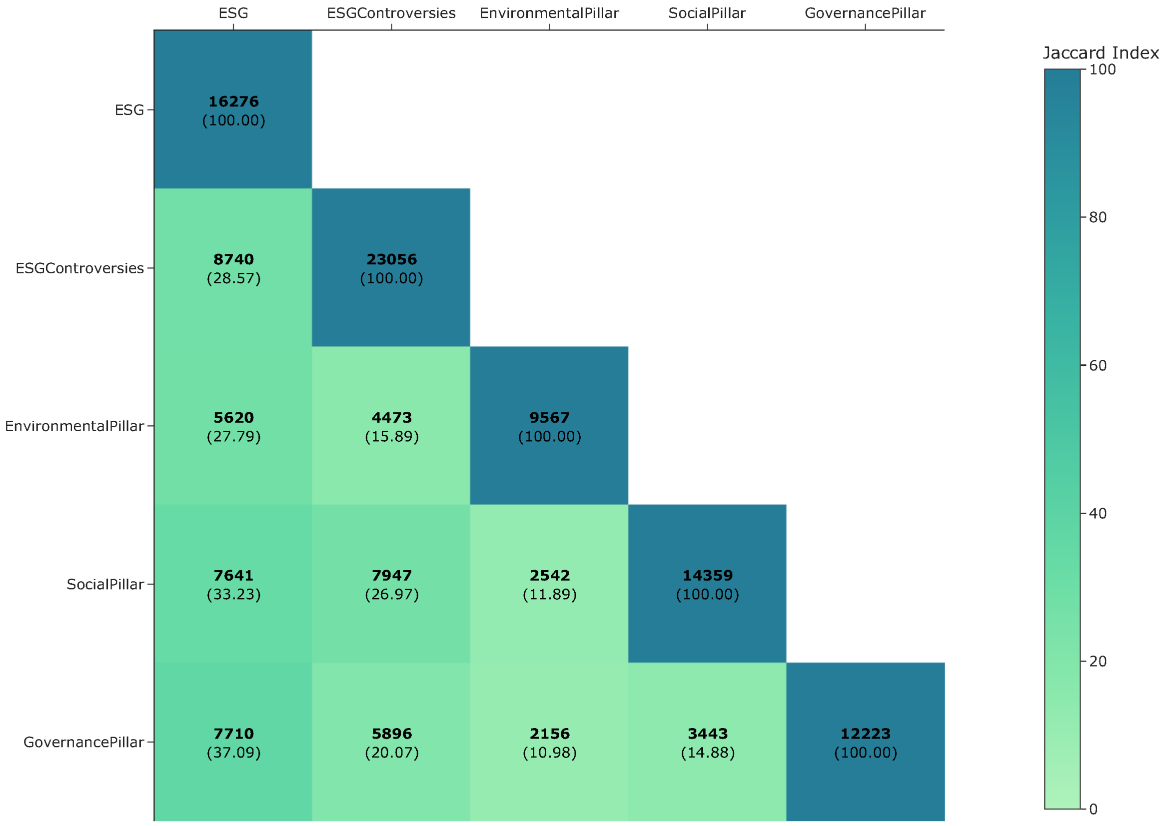
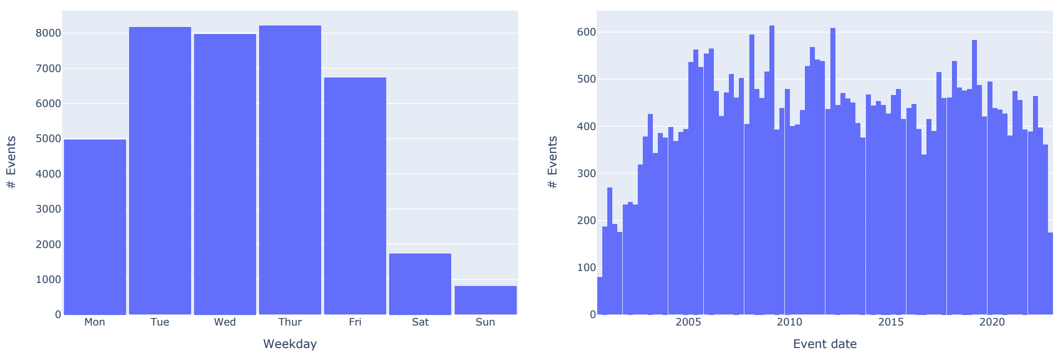


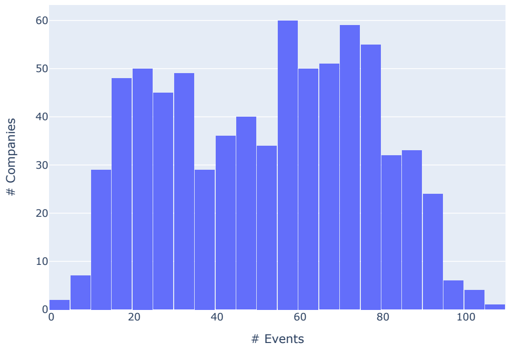
FIGURE 7: **Co-occurrence matrix of MediaESG events on the same date over the entire period.** The color scale indicates the Jaccard Index, representing the intersection over union between the sets of events corresponding to each row and column. The numbers in each cell corresponds to the total number of overlapping events (the intersection) with the numerical value of the Jaccard Index in brackets underneath.



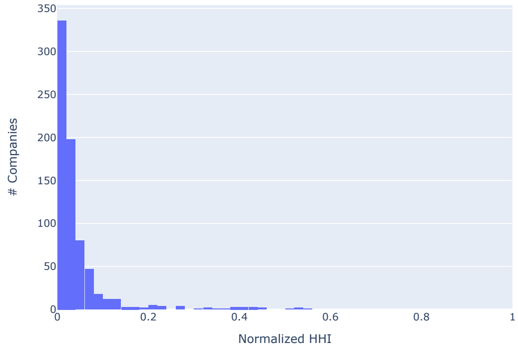
(A) Weekday distribution

(B) Sample period distribution

FIGURE 8: **Temporal distribution of identified events throughout the sample period.** The left figure illustrates the distribution of events by the day of the week, while the right figure displays the frequency of events over time.



(A) Inter-Company Event Distribution



(B) Intra-Company Event Distribution

Figure 9: **Cross-sectional distribution of events.** The left figure displays a histogram showing the number of events per company. In the right figure, the histogram illustrates the distribution of the normalized Herfindahl Hirschman Index across companies, with lower values indicating lower concentration within each company's history.

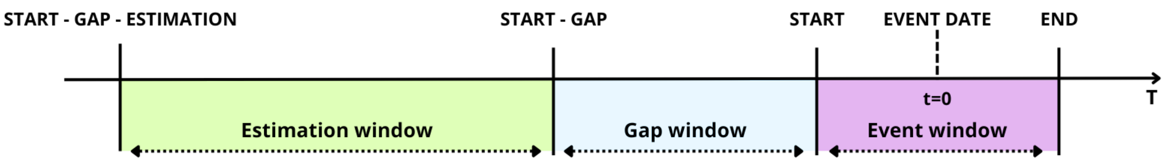


Figure 10: **Event Study Framework.** Normal returns are estimated using a specified asset pricing model (Fama-French Five Factors model in this study) on the estimation window, and then predicted on the event window. These predicted expected returns on the event window are then subtracted from the actual returns to obtain the abnormal returns over the event window. A gap window between the estimation and the event window enhances the reliability of the resulting expected returns.

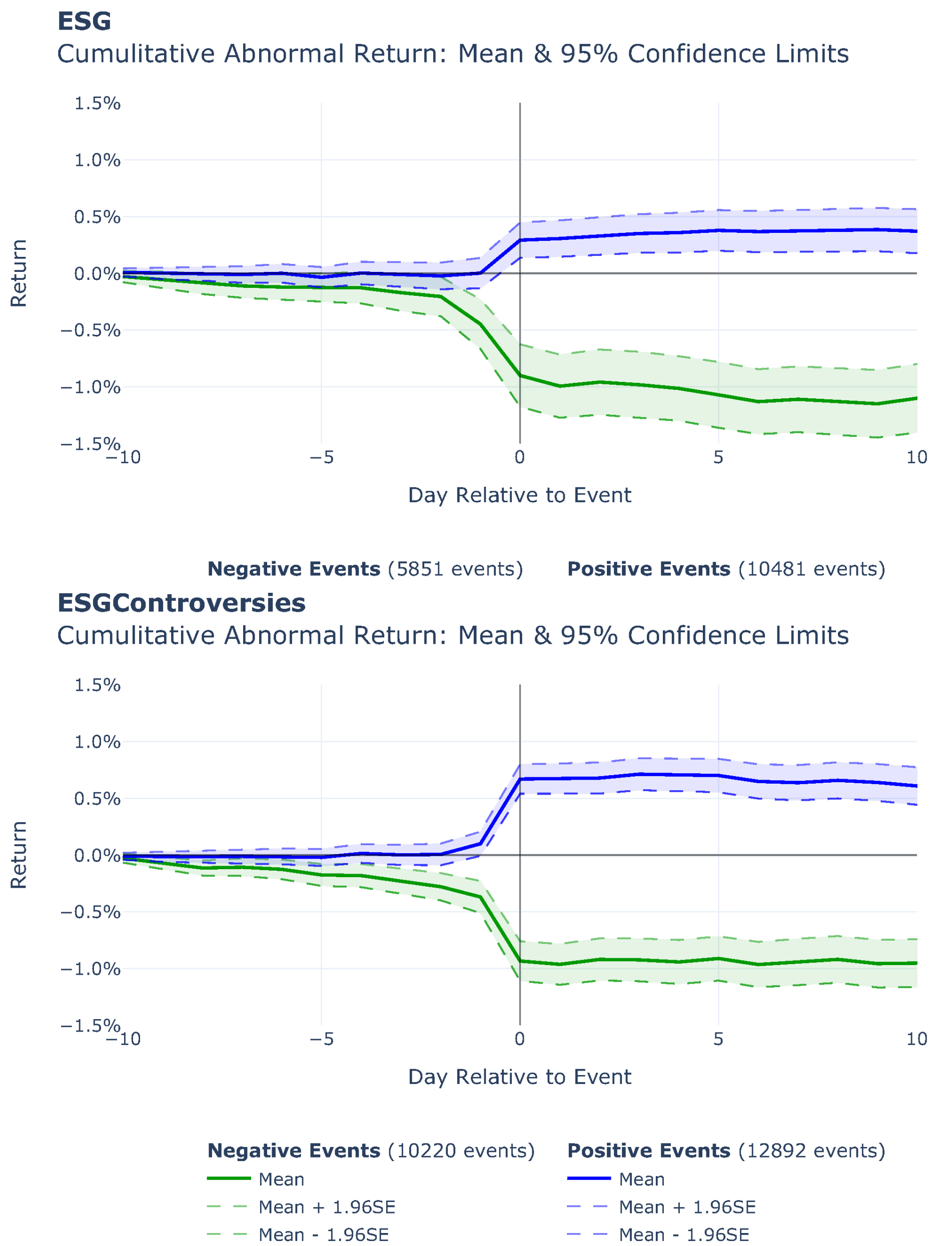


FIGURE 11: **Aggregate Results.** Cumulative Abnormal Returns (CARs) for Negative and Positive Events for the two aggregate ESG measures, ESG and ESGControversies. Each subfigure illustrates the average CARs for negative (solid green lines) and positive (solid blue lines) events, with 95% confidence intervals indicated by shaded areas and bounded by dashed lines in corresponding colors, calculated using the method in Section 4.1. The figures demonstrate differential market reactions to ESG-related events in MediaESG data, underscoring the distinct impact of negative versus positive news when contrasting ESG and ESG controversies.

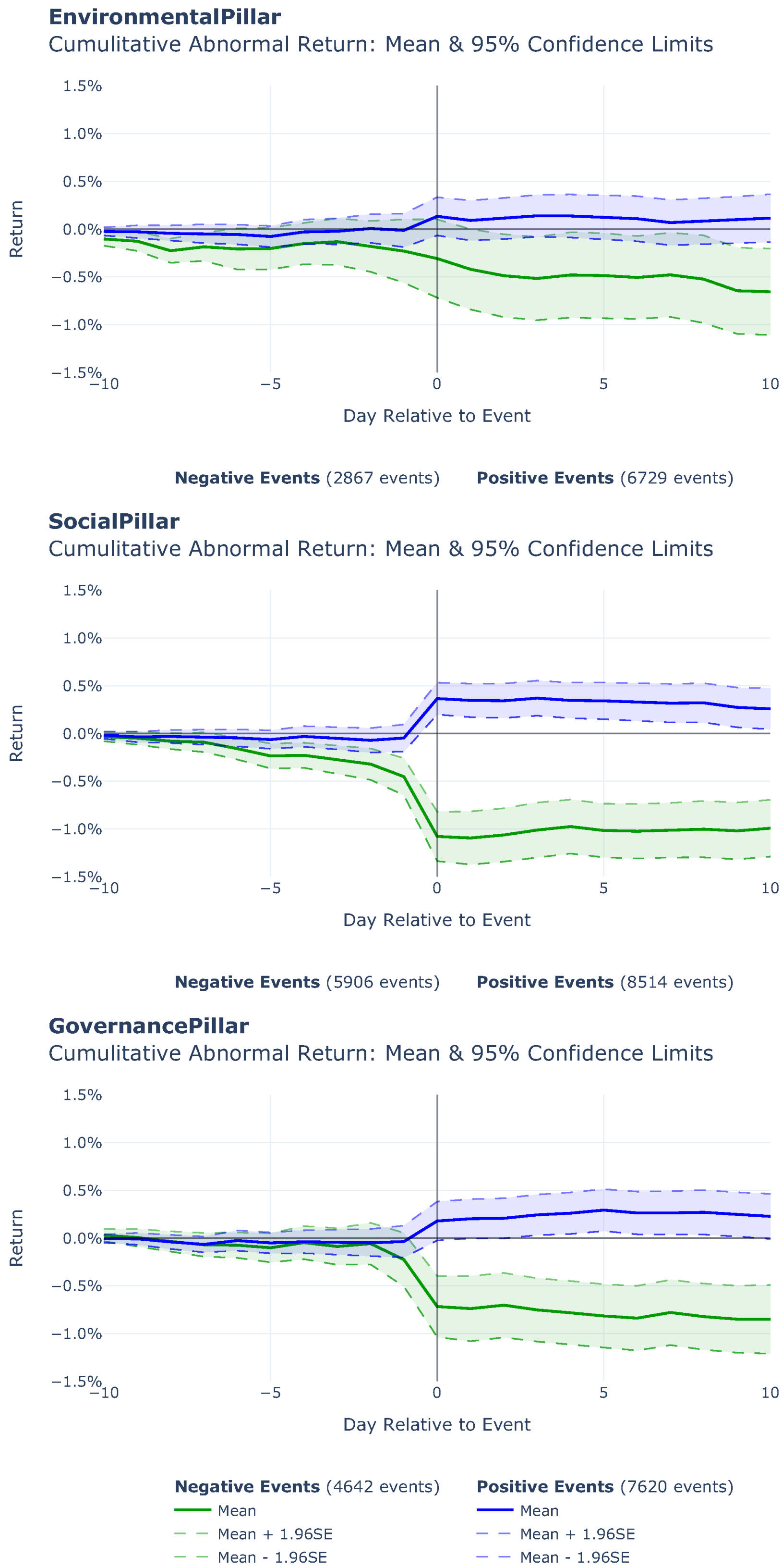


FIGURE 12: **Pillar Results.** Cumulative Abnormal Returns (CARs) for Negative and Positive Events across Environmental, Social, and Governance (ESG) pillars. Each subfigure illustrates the average CARs for negative (solid green lines) and positive (solid blue lines) events, with 95% confidence intervals indicated by shaded areas and bounded by dashed lines in corresponding colors, calculated using the method in Section 4.1. The figures demonstrate differential market reactions to ESG-related events in MediaESG data, underscoring the distinct impact of negative versus positive news in each ESG pillar.

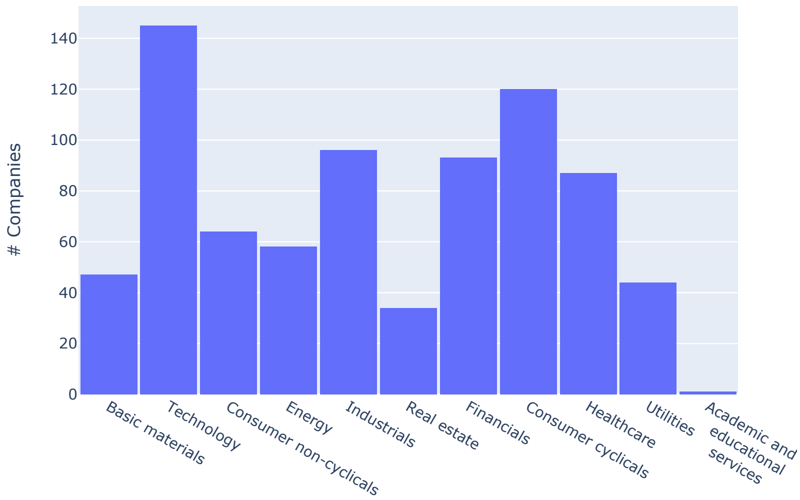


FIGURE 13: **Industry Distribution.** The distribution of sample companies across the 11 TRBC economic sectors.

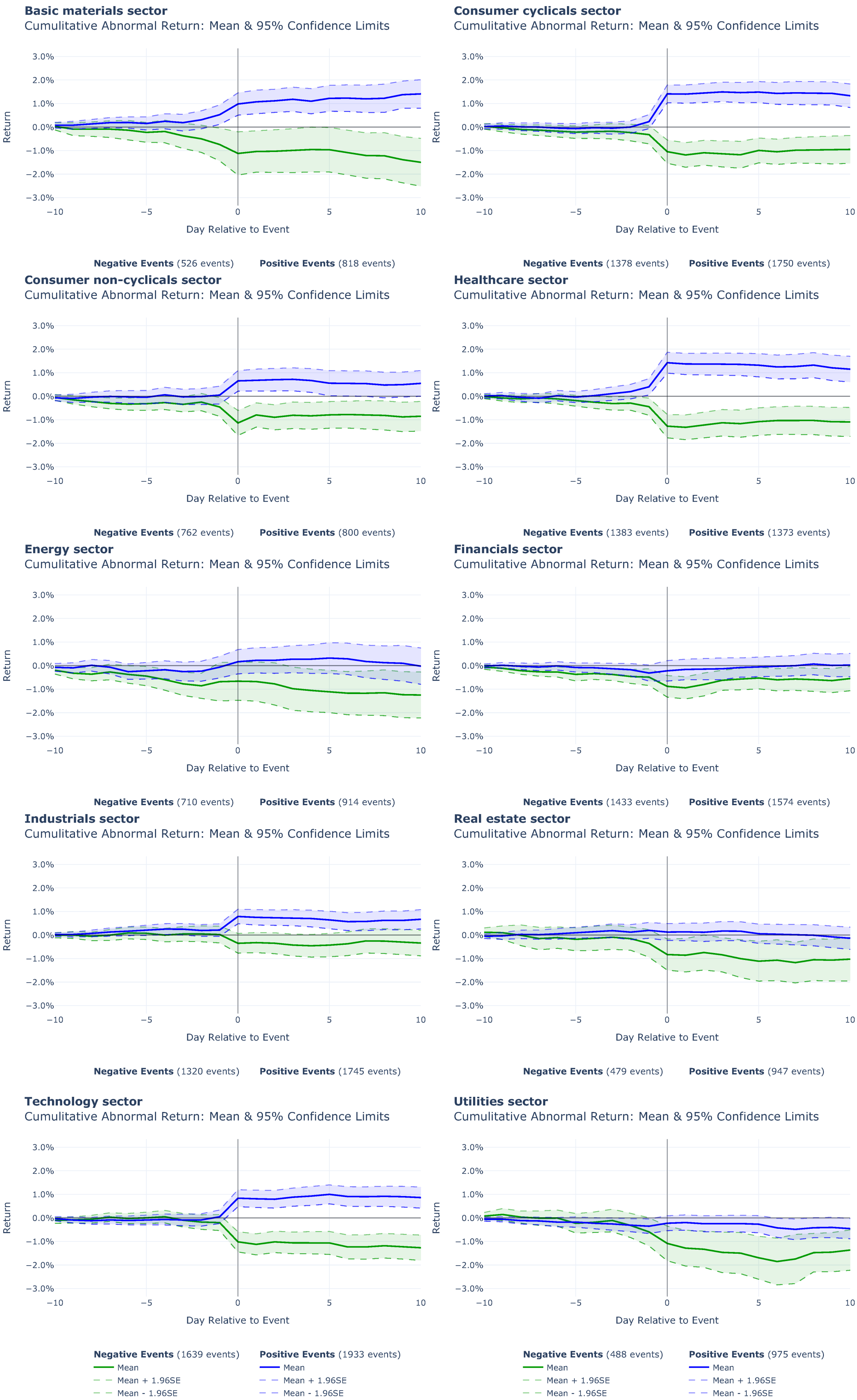


FIGURE 14: **Results by industry.** Mean Cumulative Abnormal Returns for negative events (solid green lines) and positive events (solid blue lines) for the (aggregate) ESGControversies measure, when events are decomposed into industries. A 95% confidence interval is indicated by shaded areas and bounded by dashed lines in corresponding colors, calculated using the method in Section 4.1.

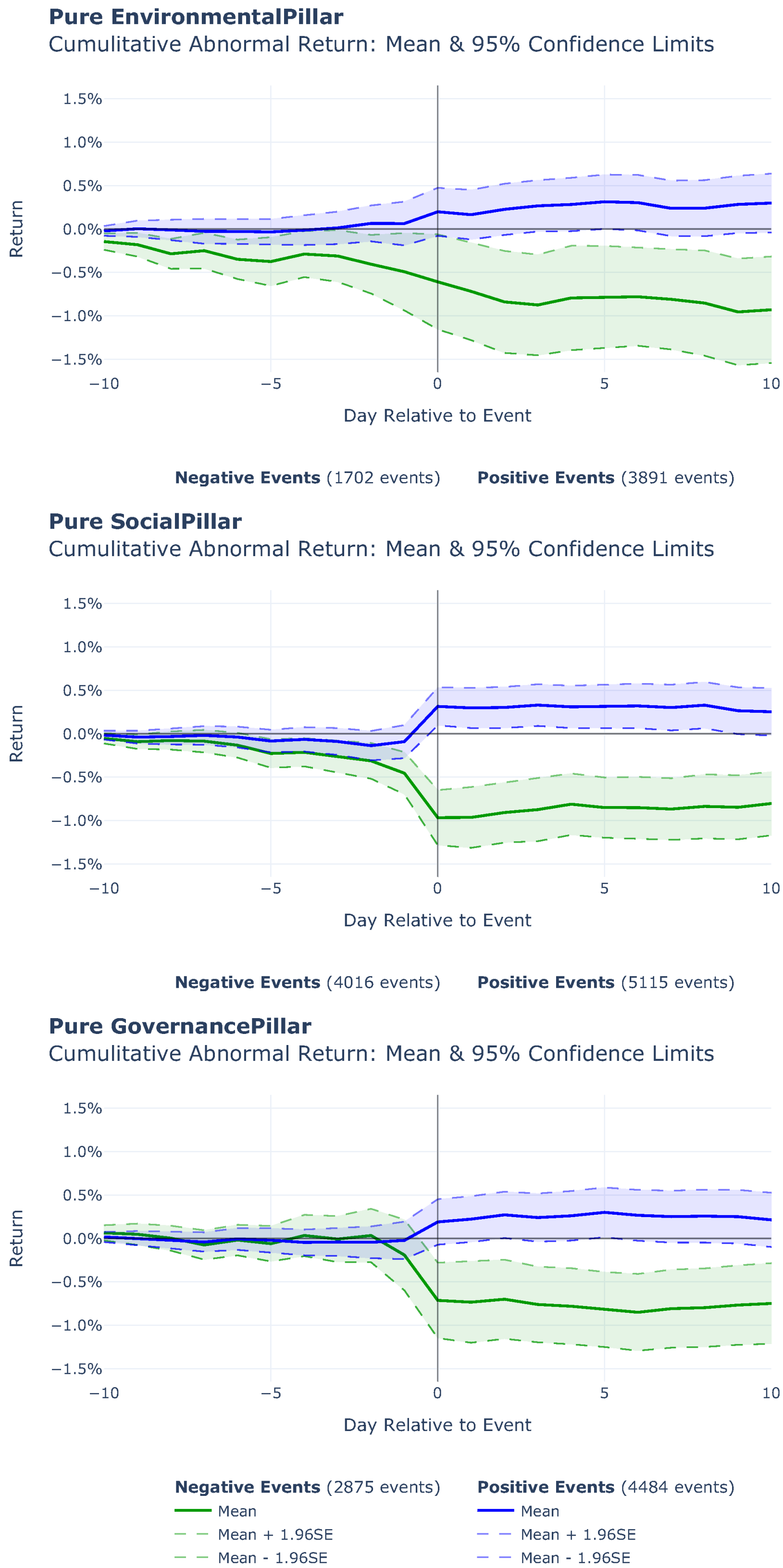


FIGURE 15: **Pure Pillar Results.** Cumulative Abnormal Returns (CARs) for Negative and Positive Events across Environmental, Social, and Governance (ESG) pillars when no other pillar occurred. Each subfigure illustrates the average CARs for negative (solid green lines) and positive (solid blue lines) events, with 95% confidence intervals indicated by shaded areas and bounded by dashed lines in corresponding colors, calculated using the method in Section 4.1.

Internet Appendix to

Public perception, identification, and market impact of ESG events

(Not for publication)

This Internet Appendix presents supplementary material and results not included in the main body of the paper.

A Refining the Scope of ESG Event Analysis

It is plausible to assume that days identified as ESG-relevant event days might also coincide with other significant corporate announcements. To investigate this, we analyze the frequency and timing of various corporate events, the details of which are presented in Table A.1. This Non-ESG related event data was retrieved from the Refinitiv Eikon database using the fields: `TR.EventStartTime`, `TR.EventStartDate`, `TR.EventType`, and `TR.EventTitle`. Table A.1 provides descriptive statistics for the Non-ESG event dataset. Events such as Earnings Releases and Ex-Dividends are distinctly non-ESG related and have been excluded from our analysis. Conversely, the nature of events labeled as "Conference Presentation" remains ambiguous, as they may include discussions on ESG topics. Therefore, in our benchmark analysis, we exclude only those events that are clearly unrelated to ESG concerns.

*** Insert Table A.1 about here ***

B Sensitivity to hyper-parameters

The event detection algorithm, defined in Section 3.1, involves four hyper-parameters:

- $\boldsymbol{k}$ – Shock magnitude for Buzz and Score features
- $\boldsymbol{q}$ – Buzz level on the day of the event
- $\boldsymbol{h}$ – Estimation window to calculate historical standard deviation
- $\boldsymbol{Z}$ – Number of look-back days

Importantly, even though the shock magnitude k has been applied to both Buzz shock and Score shock conditions defined in Section 3, it does not necessarily have to be the same parameter applied to both shocks. Thus, for the robustness, we separately define k_b and k_s as the shock magnitudes for the Buzz and Score features, respectively.

In addition to the event-detection hyperparameters, we also conduct a robustness analysis for the choice of event window in our event-study approach, defined in Section 4.1.

B.1 Sensitivity to k_b, k_s and q

We visualize the sensitivity of each MediaESG score to hyperparameters k_b, k_s, and q, through a heatmap, with the color bar representing the mean CAR over the 21-day window for each combination of hyperparameters, while keeping parameter h equal to 90 days. Only significant market reactions (p-value ≤ 0.1) are plotted on the heatmaps. The buzz shock magnitude (k_b) on the x-axis ranges from 1 to 10, indicating the minimum standardized increase in buzz required on the event date. Similarly, the shock magnitude (k_s) on the y-axis ranges from -10 to 10, where positive (negative) values signify the minimum increase (decrease) in the score required for a day to be considered as a positive (negative) event. In this context, values above (below) 0 denote positive (negative) events. Additionally, for each MediaESG score, we plot heatmaps for different minimum buzz levels (q) used in the algorithm. This parameter ensures that only events exceeding the minimum are considered as valid.

Figure A.1 provide the heatmaps for the aggregate scores, ESG and ESGControversies, respectively. Firstly, for both scores, we observe that the polarity of the event coincides with the sign of the market reactions in all cases. In other words, when the score shock magnitude parameter is above (below) zero, the market effect is also above (below) zero. Secondly, we identify a generally significant reaction to ESGControversies events, with some insignificant results for certain ESG hyperparameter settings. Finally, we note that the market reaction becomes more pronounced as any of the hyperparameters are increased in absolute value. This is evidenced by darker blue and red zones in the top right and bottom right corners of the heatmaps. As the minimum buzz level increases, we observe that the magnitude of positive and negative market reactions also becomes more pronounced. For example, the maximum reaction to positive ESGControversies events increases from 1.24% to 1.75% when the minimum buzz level increases from 10 to 100.

*** Insert Figure A.1 about here ***

*** Insert Figure A.2 about here ***

Figure A.2 provide the heatmaps for Environmental, Social, and Governance pillar scores. Regarding the Environmental pillar, we generally observe insignificant results, with a few exceptions. Importantly, we find a significant positive reaction to some negative EnvironmentalPillar events, indicated by the blue zone at the bottom right corner of the heatmaps. The effect is substantial, with a maximum ranging from 2.76% to 2.92% for different minimum buzz level settings. Interestingly, other negative events, with a buzz shock magnitude below 6, are associated with a significant and *negative* market reaction, as would be expected. Additionally, we note some significant and positive market reactions for positive Environmental events as well.

The blue zone at the bottom of the EnvironmentalPillar heatmap could be explained by several factors. Firstly, it may be due to the limited number of events (164 events with $k_s = -3$ and $k_b = 9.5$), which is approximately 16 times smaller than in the baseline results (2867 events with $k_s = k_b = 3$). This smaller sample size could make the observed effect more variable and less conclusive. Moreover, the smaller size makes these events more susceptible to co-occurrences with other pillars, which can lead to heterogeneous results as discussed in Section 4.5. Specifically, for this zone, we found that around 67% of events co-occur with at least one Social or Governance pillar event (given $|k_s| = 3$). In any case, this phenomenon could be further explored in future research.

For the Social pillar, we generally observe a significant market reaction to both positive and negative events, aligning with the polarity of the event. Most combinations observed for negative events exhibit a significant and negative reaction in the market. Additionally, we note that the effect becomes more pronounced as any of the hyperparameters are increased in absolute values.

For the Governance pillar, we find that the polarity of the events aligns with the sign of the market reaction. While many insignificant results are observed, some unique cases stand out. Firstly, the market reaction to positive GovernancePillar events becomes more pronounced with increasing buzz level and buzz shock magnitude parameters, while score shock magnitude remains moderate. Secondly, the most significant negative market reaction is observed when both buzz and score shock magnitudes are at moderate levels.

B.2 Sensitivity to h

In Figure A.3, we illustrate the sensitivity of results to varying values of the estimation window size, while keeping the rest of the hyper-parameters at their benchmark settings ($k_s = k_b = 3$, $q = 10$, $Z = 20$). The top figure displays the sensitivity of positive events, while the bottom one depicts the sensitivity of negative events. Diamond markers indicate cases where the estimated CAR reactions are significant (p-value ≤ 0.1).

For ESG and ESGControversies, the results remain significant across the entire range of h, showing relatively constant patterns.

Across the pillars, we observe heterogeneity in the findings. Negative Social pillar events appear unaffected by changes in the hyper-parameter h, while there are regions of insignificance observed for positive events. For the Governance pillar, findings are generally insignificant for positive events but significant for all levels of h for negative events. No significant results are found for positive Environmental events, while negative events generally exhibit significant reactions for smaller estimation window sizes.

*** Insert Figure A.3 about here ***

B.3 Sensitivity to Z

With baseline settings ($k_s = k_b = 3$, $q = 10$, $h = 90$), we depict the sensitivity of our estimated CAR[-10, 10] to the hyperparameter Z, representing the length of the no re-occurrence window, in Figure A.4. The upper and lower sub-figures display estimates across different MediaESG scores for positive and negative events, respectively. Diamond markers indicate cases where the estimated CAR reactions are significant (p-value ≤ 0.1).

Overall, there is minimal change in both the magnitude and significance of CAR[-10, 10] with variations in the hyperparameter Z, except for a few exceptions. The impact of positive GovernancePillar events diminishes and loses significance as the look-back window increase. Conversely, the impact of positive ESGControversies events slightly rises from 0.6 to nearly 0.8 CAR[-10, 10] with an increase in the number of look-back days.

*** Insert Figure A.4 about here ***

Since the hyper-parameter can significantly impact the number of events identified, Table A.2 presents the number of events for each value of Z. We observe that as Z increases, the number of events typically decreases, often by about half. However, even with $Z = 180$, the volume of events remains relatively large, with the smallest number being 1,861 for negative Environmental pillar events.

*** Insert Table A.2 about here ***

B.4 Sensitivity to Event-Window size

In the Table A.3, we present the estimated market reaction to events identified using our benchmark settings ($k_s = k_b = 3$, $q = 10$, $h = 90$, $Z = 20$) for various event windows of 3, 7, 11, and 21 days. Panel A shows the sensitivity of positive events to the choice of event window and Panel B the sensitivity of negative events.

Panel A reveals that, for aggregate ESG and ESGControversies scores, the reactions are significant and similar across most event windows. Among the Pillars, positive Environmental Pillar events generally show no significant reaction to the event window size, while Social and Governance Pillars exhibit significant effects across most windows.

Panel B reveals a slightly different pattern for negative events. Both ESG and ESGControversies show significance and increased magnitude sensitivity to the event window size. Social and Governance Pillars display similar trends, with significance and increasing magnitude as the window lengthens. For the Environmental Pillar, effects are significant and negative for several event windows, with magnitude also increasing with the event window.

Since reactions are expected to vary with event window size, we confirm that our findings are not solely dependent on the choice of event window, as significance and appropriate magnitudes are observed across most settings. We do not provide results for event windows greater than 21 days, as they are more prone to noise and not central to our study, which focuses on short-term effects.

*** Insert Table A.3 about here ***

Tables and Figures

Company Event Type	# Events	# Companies	Yearly Average
EarningsReleases	23991	671	4.0
ConferencePresentations	22875	659	4.5
ExDividends	15193	518	4.0
ShareholderAndAnnualMeetings	3683	588	1.1
CorporateCallsAndPresentations	3498	578	1.9
EarningsCallsAndPresentations	1961	382	1.8
CorporateAnalystMeetings	1397	383	1.2
CorporateSalesRelease	835	55	4.2
Conferences	520	90	3.4
MergerAndAcquisitionCallsAndPresentations	512	231	1.1
SpecialDividendsCash	450	76	3.3
OtherCorporate	426	32	4.9
StockSplits	367	256	1.1
SalesConferenceCall	158	16	4.3
CompanyVisits	120	42	2.4
GuidanceCallsAndPresentations	90	57	1.2
BrokerageAnalystMeetings	87	53	1.4
ExtraordinaryShareholdersMeeting	77	68	1.0
RegularDividendsStock	49	10	3.8
CorporateInvestorRoadshow	46	25	1.5
BrokerageAnalystCalls	37	30	1.1
SyndicateRoadshows	25	11	1.8
CapitalGainsCash	10	1	3.3
GuidancePresentation	9	7	1.3
CorporatePresentation	9	7	1.3
SalesAndTradingStatementReleases	8	7	1.0
OtherDividendsCash	7	3	2.3
RegularDividendCashWithAlternative	5	2	2.5
IndustrySpecificCall	4	4	1.0
EarningsPresentation	3	3	1.0
M&APresentation	2	2	1.0
SalesPresentation	2	2	1.0
SecondaryFilings	2	1	2.0
IndustrySpecificPresentation	1	1	1.0
TradingStatementPresentation	1	1	1.0

TABLE A.1: Descriptive statistics on Non-ESG events data and our assumption on whether detected events occurring on these days are excluded from our analysis or not. Highlighted in bold are excluded events.

	Look-back window Z							
	10	20	30	60	90	120	150	180
PANEL A: POSITIVE EVENTS								
ESG	10959	10481	10054	8997	8113	6772	5765	4907
ESGControversies	13680	12892	12171	10489	8960	6812	5475	4339
EnvironmentalPillar	6908	6729	6570	6157	5737	5164	4718	4276
SocialPillar	8875	8514	8165	7347	6651	5590	4787	4134
GovernancePillar	7857	7620	7415	6883	6426	5629	5075	4512
PANEL B: NEGATIVE EVENTS								
ESG	6114	5851	5636	5159	4715	3982	3505	3030
ESGControversies	10823	10220	9612	8280	7084	5588	4584	3723
EnvironmentalPillar	2947	2867	2808	2664	2512	2221	2039	1861
SocialPillar	6166	5906	5668	5194	4746	4097	3663	3222
GovernancePillar	4789	4642	4532	4238	3938	3486	3190	2854

TABLE A.2: **Number of events per Z** The table presents the number of events identified using the algorithm while varying the hyper-parameter Z from 10 to 180 days.

Event Window	Aggregate: ESG	Aggregate: ESGControversies	Pillars: (E)	Pillars: (S)	Pillars: (G)
Panel A: Positive Events CAR					
$[-1,\ 1]$	0.33% ***	0.67% ***	0.09%	0.41% ***	0.26% ***
$[-3,\ 3]$	0.35% ***	0.70% ***	0.17% *	0.38% ***	0.29% ***
$[-5,\ 5]$	0.38% ***	0.71% ***	0.17% *	0.37% ***	0.33% ***
$[-10,\ 10]$	0.37% ***	0.61% ***	0.12%	0.26% **	0.23% *
Panel B: Negative Events CAR					
$[-1,\ 1]$	-0.79% ***	-0.69% ***	-0.24%	-0.78% ***	-0.68% ***
$[-3,\ 3]$	-0.86% ***	-0.75% ***	-0.37% **	-0.79% ***	-0.71% ***
$[-5,\ 5]$	-0.94% ***	-0.79% ***	-0.28%	-0.86% ***	-0.74% ***
$[-10,\ 10]$	-1.10% ***	-0.95% ***	-0.66% ***	-0.99% ***	-0.85% ***

Table A.3: **Market Reaction Sensitivity to Event-Window Size** The table presents the estimated Mean CAR across various event window sizes. Panel A and Panel B show how market reactions vary with different event window sizes for positive and negative events, respectively. Symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

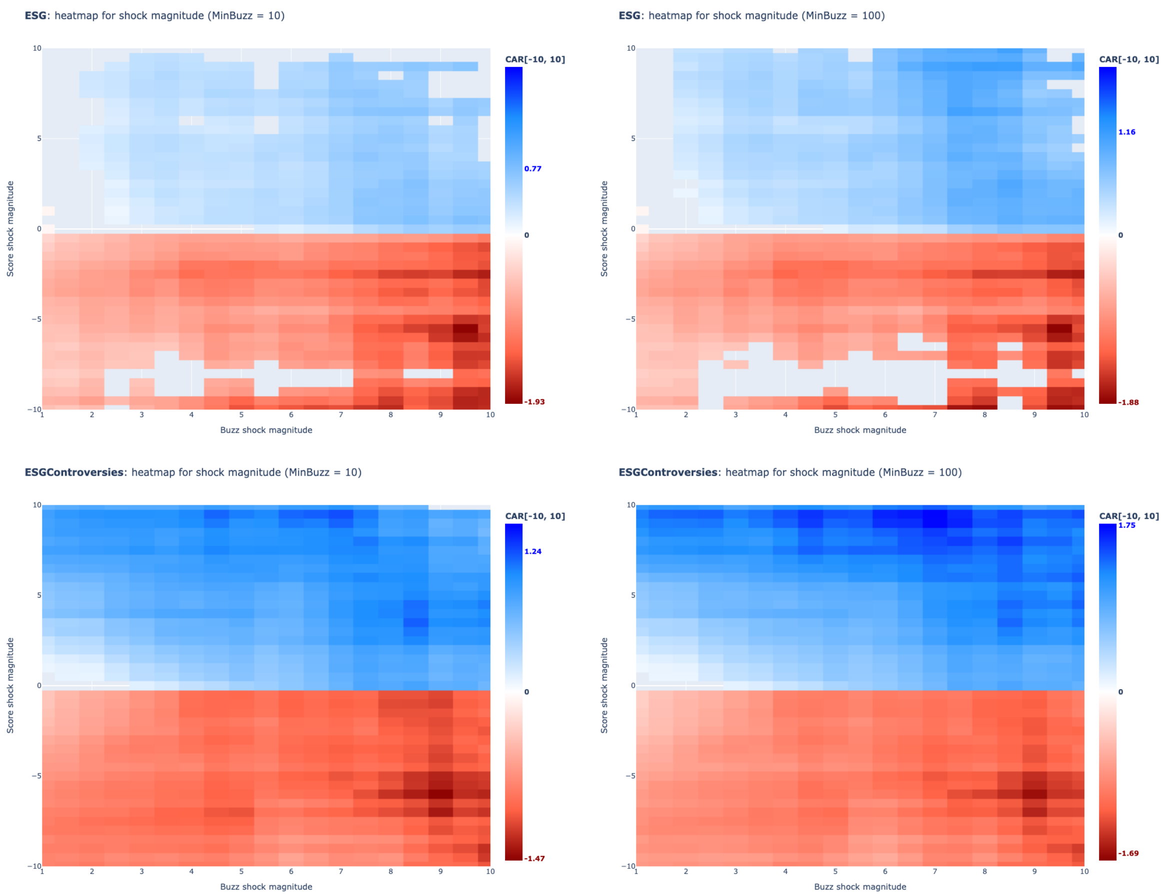


FIGURE A.1: **ESG and ESGControversies sensitivity to k_b, k_s and q.** Each heatmap depicts CAR estimates obtained over the entire 21-day window for various combinations of hyper-parameters. Only the combination achieving a significant CARs (with p-value ≤ 0.1) are plotted. The x-axis represents the Buzz Shock Magnitude (k_b), indicating the minimum standardized increase in Buzz relative to the historical standard deviation. The y-axis represents the Score Shock Magnitude (k_s), denoting the minimum standardized increase (decrease) in Sentiment Score relative to the historical standard deviation for positive (negative) k_s values. In other words, k_s above (below) 0 shows the reaction to positive (negative) score events. The heatmaps for the same score differ in the minimum Buzz level (q) defined by the algorithm, as described in the title.

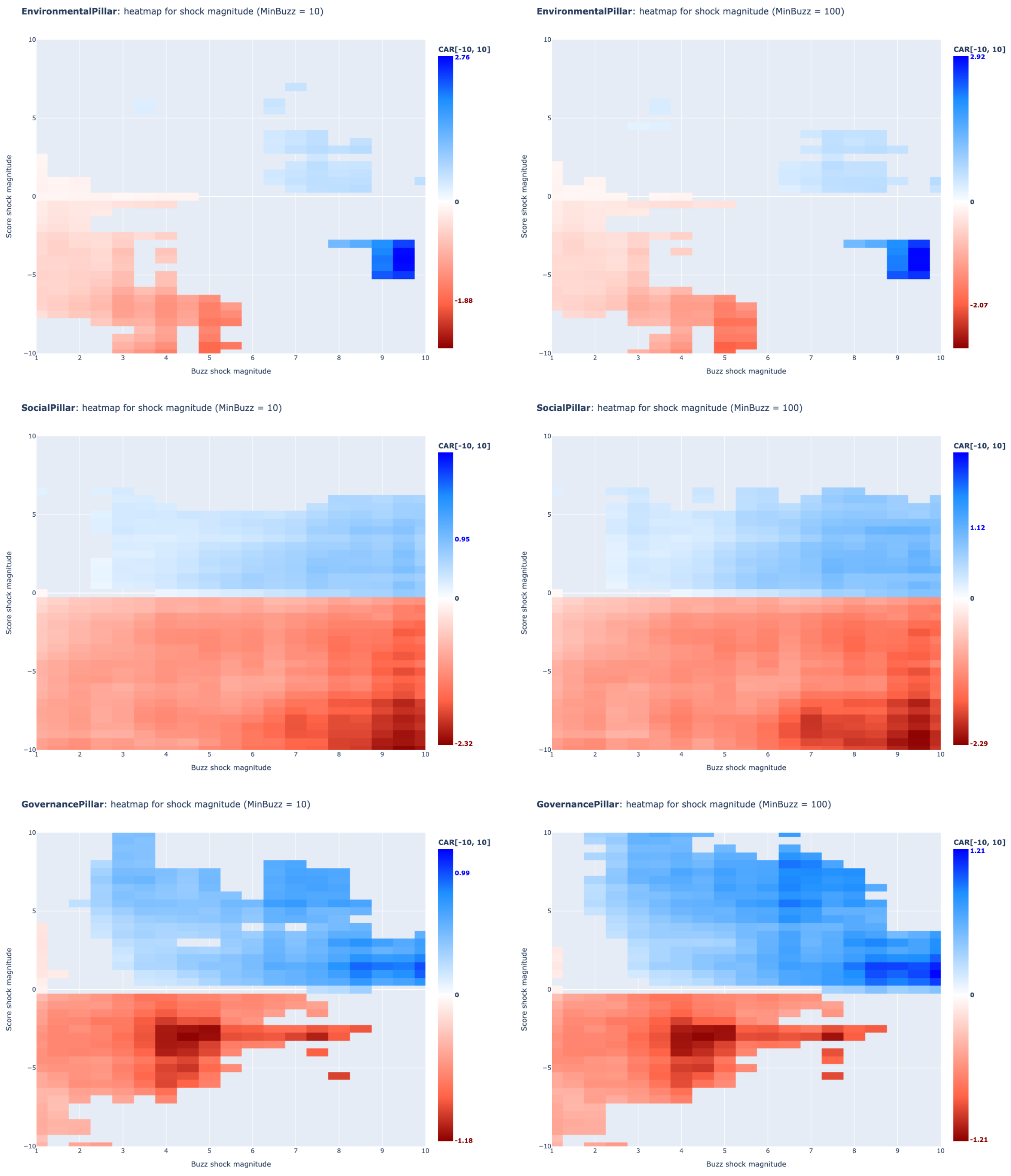


FIGURE A.2: **Pillar sensitivity to k_b, k_s and q.** Each heatmap depicts CAR estimates obtained over the entire 21-day window for various combinations of hyper-parameters. Only the combination achieving a significant CARs (with p-value ≤ 0.1) are plotted. The x-axis represents the Buzz Shock Magnitude (k_b), indicating the minimum standardized increase in Buzz relative to the historical standard deviation. The y-axis represents the Score Shock Magnitude (k_s), denoting the minimum standardized increase (decrease) in Sentiment Score relative to the historical standard deviation for positive (negative) k_s values. In other words, k_s above (below) 0 shows the reaction to positive (negative) score events. The heatmaps for the same score differ in the minimum Buzz level (q) defined by the algorithm, as described in the title.

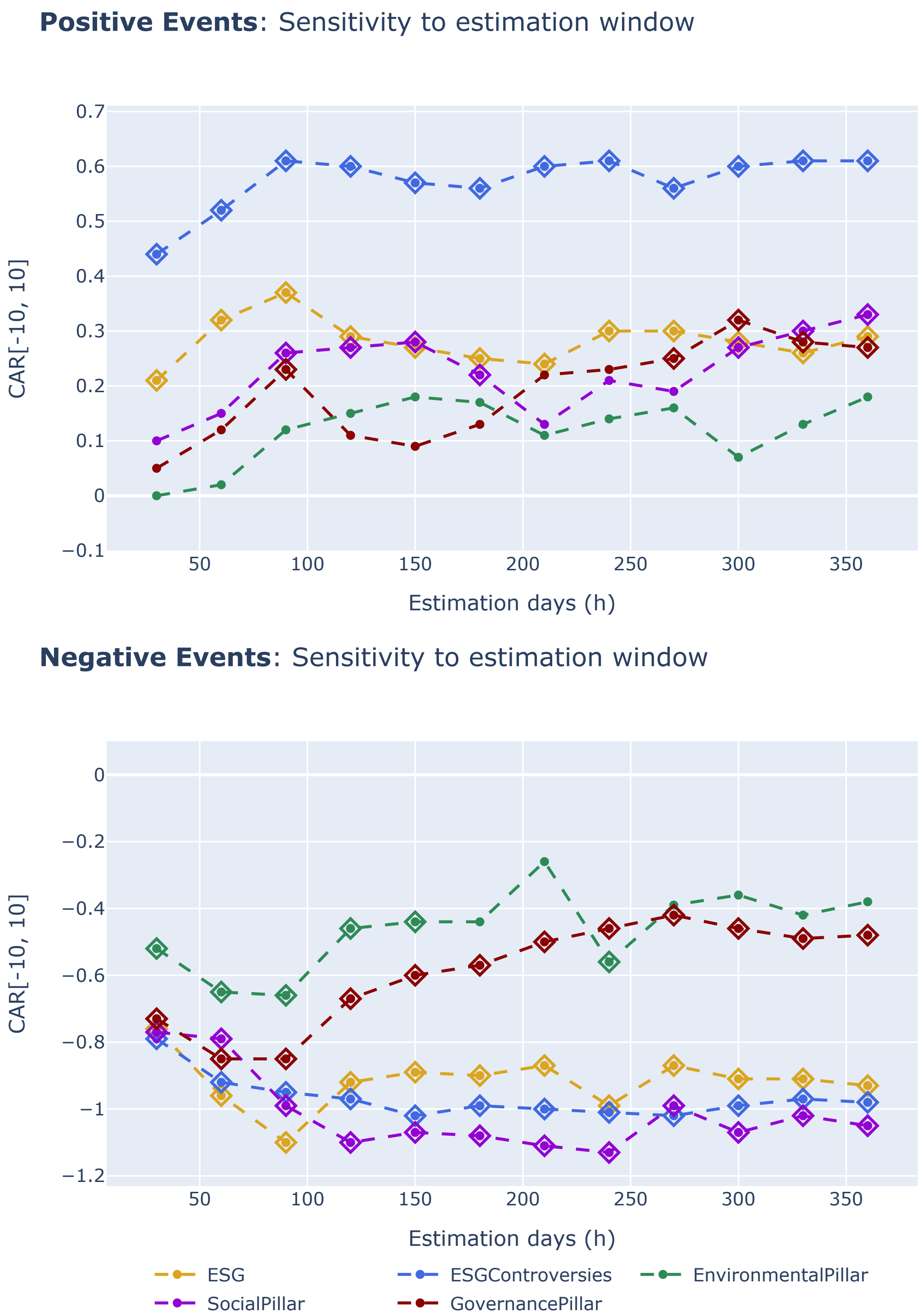


FIGURE A.3: **Sensitivity to the estimation window.** Both graphs depict the mean CAR reaction over the 21-day period for all five scores across various estimation window values. The upper graph illustrates the sensitivity of positive events, while the lower graph illustrates the sensitivity of negative events. When the estimated CAR effect is significant (p-value ≤ 0.1) it is denoted with a diamond marker.

FIGURE A.4: **Sensitivity to the lookback window** Z**.** Both graphs depict the mean CAR reaction over the 21-day period for all five scores across various look-back window values. The upper graph illustrates the sensitivity of positive events, while the lower graph illustrates the sensitivity of negative events. When the estimated CAR effect is significant (p-value ≤ 0.1) it is denoted with a diamond marker.