Master in Management – Majeure Finance

Research Paper

The Impact of Retail Investor Attention on Event Returns of ESG Scandals

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Abstract

This paper uses ESG incident data to investigate the predictive power of retail investor attention for abnormal returns during ESG scandals. I measure attention through stock ticker searches in Google and show that retail attention significantly correlates with higher event window returns. However, most abnormal returns are realised before the event day, which causes some reverse causality concerns that may be addressed in future research. Finally, I also show that retail attention is a significant predictor of post-event drift, which is robust to the seriousness of the event and event returns as control variables. These findings support the hypothesis that individual investors voice their disagreement with poor ESG practices by selling offending companies' stock, while consumers follow suit by taking action that further reduces company value.

1. Introduction

ESG integration in investing has become commonplace over the last decade. In a review of the PRI (UN Principles of sustainable investing), Gibson Brandon et al. (2022) find that, globally, at the end of 2021, $120 trillion in assets were under management by its signatories. These include large asset owners like CalPERS or investment managers like BlackRock. Despite market-wide fund outflows and pushback over greenwashing concerns in 2022, ESG funds saw net inflows[1]. Still, considerable disagreement remains about optimal ESG investing practice and even the definition and measurement of good ESG practice. For instance, in 2022, the US-based Sustainable Investment Forum amended its methodology of identifying "ESG assets". This change resulted in a drastic reduction from $17.1 trillion to $8.4 trillion (US SIF (2022)). Similarly, disagreement persists in ESG ratings (Chatterji et al. (2016)), with recent findings indicating that disagreement tends to increase with more disclosure (Christensen et al. (2022)). Considering these ambiguities about what constitutes virtuous behaviour by corporates and how ESG investment can be measured, it is of little surprise that the implications of ESG for firm value are also not yet fully understood.

My paper aims to investigate some of these impacts of ESG on firm value. In particular, my focus is on the interaction between retail investor attention and large ESG scandals. In the face of disagreement among professional ESG analysts, I ask whether the attention of individual financial market participants is a good predictor for negative stock returns of firms facing ESG concerns. To answer this question, I refer to Google search volume to measure retail investor attention (see Da et al. (2011)) and ESG incident data from Swiss data provider RepRisk to identify ESG scandals. This type of incident data has the advantage of being a realised measure of past ESG failures and has also demonstrated its strength as a predictor of poor future ESG practice (Glossner (2021)). Further, I expect retail investors to pay more attention to ESG incident news rather than ESG ratings or their changes.

[1] https://lipperalpha.refinitiv.com/reports/2023/01/everything-green-flows-2022-reports-of-esgs-death-are-much-exaggerated/#, checked on Jun 11, 2023

I hypothesise that abnormal returns around ESG incidents may be sensitive to retail investor attention and beliefs. Previous research already investigated the reaction of investors and consumers to ESG concerns. For instance, Servaes and Tamayo (2013) highlight that firms with high public awareness suffer losses in value when faced with ESG concerns. In contrast, this link is less significant for firms outside the public perception. In another example, Choi et al. (2020) show individual investors adjusting their beliefs about climate change when faced with abnormally high temperatures in their city. Under such circumstances, individual investors pay more attention to carbon-intensive stocks, which underperform in the month of the temperature spike. The channel affecting stock prices is found to be selling pressure of individual traders who are looking to curb their exposure to climate-unfriendly companies.

In my study, I perform tests to establish a comparable connection and investigate whether the attention of retail investors can predict abnormal negative returns after ESG incidents. Of course, ESG scandals contain more information about firm fundamentals than unusually hot temperatures, and changes in fundamentals (e.g., lawsuits, fines, or future increases in costs) may explain part of the price movements seen around ESG incidents. However, these incidents could also be a catalyst for individual investors or consumers to act on their discontent with a firm's behaviour, causing price declines through selling stock or boycotting the firm's products. The analysis I conduct is twofold. First, I use a standard event study methodology to document abnormal returns around ESG incidents. In the second step, I examine investor attention around ESG incidents. Specifically, I test if Google search volume significantly predicts event returns and post-event drift in cross-sectional regressions.

My event study results confirm prior findings established by Glossner (2021), who uses largely the same RepRisk dataset of ESG incidents. I find significantly negative cumulative abnormal returns (CARs) in 21- and 31-day event windows around ESG scandals. The losses ranging from 1.6% to 3.8% (for the most serious scandals) provide evidence that ESG incidents destroy firm value. Beyond CARs in these "narrow" event windows, I study post-event drift and time series of abnormal returns. Two findings result from these additional tests, which diverge from the steps taken by Glossner (2021). First, market reactions appear to lead the publication of news relating to ESG incidents, as most abnormal returns around the event are realised before the event day. Second, the ESG incidents show economically meaningful drift up to day 60 after the event, although this result is generally significant only for the largest scandals.

Next, I examine the predictive power of retail investor attention for CARs. I test my stated hypothesis that greater attention during the week of an ESG scandal results in higher event returns and higher post-event drift. The results of cross-sectional regressions show both statistically and economically significant coefficients for investor attention in regressions of CAR in the 21- and 31-day windows. As previously established, returns during these windows are mostly realised *before* the ESG scandal. Therefore, reverse causality concerns remain around this part of my results.

Finally, I also find that Google search volume is a significant and economically important predictor of post-event drift, which a reverse causality story cannot easily explain. Separate robustness checks in the final part of my paper confirm this finding. I test the robustness of my attention measure in regressions controlling for the event's seriousness (as determined by RepRisk) and CARs in a window of [-15;0] trading days relative to the ESG scandal. While CARs in [-15;0] perform relatively well as predictors of drift following very large scandals, Google search interest does not lose its significance. Overall, my results indicate that stronger attention from retail investors on ESG scandals predicts future losses realised as post-event drift.

Although I document a significant link between individual investor attention and negative abnormal stock returns, my study does not resolve the question through which channel these losses occur. For instance, Choi et al. (2020) find that abnormally warm weather induces individual investors to become more socially responsible and sell the stock of carbon-intensive firms. A similar mechanism could also be at play in the case of ESG scandals. The publication of ESG incident news to an attentive investing public may cause investors to sell affected stocks for ethical reasons. Other potential channels to affect firm value include changes to firm fundamentals caused directly by the ESG incident and indirect effects on future cash flows like consumers boycotting the offending firm. Investigating these channels could be the subject of future research.

2. Related Literature

This paper relates to two families of academic literature: the first examines financial markets in the presence of investors with attention constraints, while the second emerged more recently and studies ESG investing.

Behavioural finance literature generally follows the paradigm defined by Kahneman (1973), who describes attention as a limited cognitive resource that can be divided between tasks and requires conscious effort. This finding has had wide-ranging consequences on the academic study of financial markets. In theoretical research, Hirshleifer and Teoh (2003) model the impact of limited attention on firm choices about the disclosure of information and financial reporting. Peng and Xiong (2006) build a theoretical framework of attention allocation among investors. They document "category-learning" as an essential consequence of limited investor attention: the tendency of investors to closely follow market- and sector-wide information while being more inattentive to firm-specific news.

Limits to attention have also been studied extensively in empirical finance research. Attention tends to be particularly pertinent for describing the behaviour of individual investors. For instance, Barber and Odean (2008) show the impact of attention on the trading behaviour of both individual and institutional investors. Their findings indicate that individual traders' potential set of stocks to purchase is heavily skewed towards those attracting the most attention. They further stress that institutional investors are much less prone to attention-driven buying. However, other studies also provide evidence for the limits to professional investor attention. For instance, Corwin and Coughenour (2008) show that NYSE specialist traders face attention constraints when providing liquidity for the stocks they cover.

A significant subsection of the literature examines the interaction between attention and the predictability of returns in momentum strategies or post-event drift (e.g., following earnings announcements). This research area is relevant to this study due to my examination of drift in stock returns after ESG scandals. Cohen and Frazzini (2008), for instance, demonstrate that investors pay too little attention to news affecting companies that are economically linked through customer-supplier relationships. Consequently, companies whose supplier has been the subject of negative news tend to experience underreaction and predictable stock prices.

Generally, the scientific consensus surrounding price and earnings momentum (i.e., post-announcement drift) favours explanations based on investor under- and overreaction, depending on the level of investor attention. These concepts are outlined by Hou et al. (2009), who find that increased attention weakens earnings momentum (less drift) but strengthens price momentum, which shows subsequent reversal. Relatedly, Hirshleifer et al. (2009) provide evidence for their *investor distraction* hypothesis. Their paper documents weaker announcement day returns and higher drift following days with higher information loads, measured by the number of simultaneous earnings announcements.

The mentioned studies use various common measures to proxy for investor attention, including extreme stock returns, abnormal trading volume or news coverage of stocks. Such attention proxies have delivered great insight into investor behaviour. However, over the last decade, *direct measures* of attention have gained in popularity. Da et al. (2011) demonstrate the rich information content of a security's search volume in Google as a measure of attention. Multiple important findings for my paper emerge from their work: they establish the methodology for obtaining abnormal search interest from Google but also determine that Google search volume leads known proxies for attention (e.g., extreme returns, news coverage) and likely captures retail (individual) investors' attention.

Search frequency in Google as a measure of attention has since found various applications in finance literature. For instance, Niessner (2014) uses it to document strategic disclosure timing practised by managers who reveal negative news when investors are more distracted, like Fridays or days before holidays. Vozlyublennaia (2014), meanwhile, finds that long-term increased retail investor attention can reduce the predictability of returns, therefore improving market efficiency. Finally, Ben-Rephael et al. (2017) stress the importance of distinguishing between different types of attention. They provide evidence that it is not retail (Google search frequency), but institutional investors' attention (measured through Bloomberg search frequency) which alleviates post-announcement drift.

My paper also draws from the literature surrounding sustainable or ESG investing. This still relatively young field has so far produced mixed evidence on important questions such as the out- or underperformance of "green" stocks or the impact of divestment on firms with poor ESG records. For instance, Edmans (2011) finds that investors underreact to positive ESG information, such as employee satisfaction, thus leading to abnormal positive returns of firms with these traits. Similarly, Glossner (2021) hypothesises underreaction to negative ESG incidents news, which he backs up by showing negative alphas for stocks with high rates of such incidents.

Conversely, other research provides evidence for the outperformance of firms with poor ESG record. Pástor et al. (2022) empirically find lower expected returns for green assets, despite their outperformance in the past. Their study proposes a recent shift in investor taste towards greener assets, which may explain higher realised returns of green assets over the last decade. Therefore, the outperformance of green firms will also depend on the sample period used. In their study of carbon emissions and US stock returns, Bolton and Kacperczyk (2021) determine that carbon emission risk is already largely priced by investors, and dirtier firms consequently deliver higher returns when controlling for common risk factors. Finally, Gibson Brandon et al. (2021) determine that ESG rating *disagreement*, particularly in the environmental dimension, drives positive alpha. This finding may again point towards the hypothesis that investors price environmental risks.

The split in academia about ESG firms' stock performance is also reflected in discussions about ESG and firm value. Focussing on the interaction between ESG and discount rates, Heinkel et al. (2001) and Pástor et al. (2021) model investing behaviour which follows ESG criteria and find higher equilibrium costs of capital for polluting firms and those with other negative externalities. The empirical evidence regarding the impact of such behaviour is mixed. Studies such as Chava (2014) find that exclusionary ESG investing materially affects companies' cost of capital, while more recently, Berk and van Binsbergen (2021) determine that divestment strategies have little impact on the cost of capital and decision-making of firms. Finally, a strong reaction of consumers to the ESG incident may also affect expected future cash flows instead of the cost of capital. For instance, Servaes and Tamayo (2013) demonstrate that firms with greater consumer awareness are penalised in their value when ESG concerns arise. This finding is relevant to my paper, as I propose consumers reacting to ESG scandals through boycotts as an explanation for part of the abnormal losses seen after such incidents.

My paper also takes inspiration from literature using incident-based ESG ratings, specifically the measures developed by RepRisk. Incident-based rating systems are advantageous for research purposes since they are more direct measures with less room for disagreement and easily allow for conducting event studies (Glossner (2021)). Besides Glossner (2021), several other recent papers have used RepRisk ESG incident data to study firm value and CSR practice. For instance, Li and Wu (2020) use RepRisk data to build an ESG outcome measure and subsequently study the differences in CSR actions taken by public and private firms to reduce their incident levels. Focussing on ESG and firm value, Derrien et al. (2021) find that analysts revise earnings estimates downward after negative ESG incidents. They further provide evidence that these analysts are correct to lower profit expectations, i.e., their forecasting errors decrease. This indicates that considering ESG concerns is rational, as they affect future fundamentals.

3. Data and Variable Construction

3.1. RepRisk data

To identify the ESG scandals used in the event study, I refer to datasets obtained from RepRisk, which include ESG risk incidents recorded from January 2007 until August 2020. RepRisk screens a variety of sources, including print, online media, social media blogs and regulatory releases for ESG risk incidents relating to any of the 225,000 public and private companies covered by the firm. These ESG incidents are grouped into one or more of 28 categories (e.g., Animal mistreatment, Climate change, Child labour, ...) and ranked along three parameters (*Severity*, *Reach of information source* and *Novelty*) with two to three levels each. In the final process step, RepRisk assigns a quantitative measure of exposure to ESG risks over time to the responsible company through the *RepRisk Index* (RRI). The RRI is based on a proprietary algorithm and ranges from 0-100, where 0 indicates no exposure to ESG risk, and 100 signifies extreme risk exposure. A company's RRI generally increases when a new ESG risk incident is identified and decays over time in case no new incidents occur. Above a level of 25, the decay takes place at a rate of 25 every two months and below 25, the RRI reverts to zero over 18 months (RepRisk (2023)).

In total, I obtain three related datasets from RepRisk, all spanning from January 2007 to August 2020. The *RRI Shock dataset* contains around 3,200 firm-month observations corresponding to large ESG scandals, for which the RRI climbed by at least 25 over the past month. This dataset's main variable used for analysis is *RRI Trend*, which captures the one-month change in a company's RRI. Second, the *ESG News dataset* contains raw incident news dates for over 150,000 firms. The data encompasses about 600,000 separate incidents and their classification along the three mentioned parameters. Finally, the *RepRisk ID dataset* matches the internal company identifier used by RepRisk (RepRisk ID) to the unique security identifier in the CRSP database (PERMNO). A total of 3,380 RepRisk IDs are matched to over 4,000 PERMNOs in the dataset.

For each firm-month observation in the *RRI Shock dataset*, I select the event date as the first news day in the respective month (found in the *ESG News dataset*). Further, I exclude ESG incidents of RRIDs matched with multiple PERMNOs to avoid companies or exchange-traded funds with several classes of shares. Finally, I only consider observations valid if no prior ESG scandals (RRI Trend >=25) occurred for the same company within 1.4 years leading up to the event to preserve an undisturbed estimation window. Following these criteria, I identify a set of 3,045 ESG incidents for further analysis.

3.2. CRSP data

For each of the 2,300 distinct PERMNOs in the set of ESG incidents, I obtain daily holding period returns from CRSP, covering the same period as the RepRisk sample (2007-2020). After merging CRSP stock returns with the *RRI Shock dataset*, I determine the event trading days as either the event news day or the following trading day if the news day was non-trading.

To obtain the final sample of 2,156 ESG incidents for use in the event study, I undertake additional data cleaning steps. I remove events relating to stocks not listed at the time of occurrence and stocks whose time series contained large interruptions in trading (>5 calendar days difference between trading days). Finally, I only retain observations with a full estimation window of 299 trading days up to 50 trading days before the event and a full event window of 15 days pre- and post-event.

3.3. Google trends data and attention measure

Google Trends provides access to a measure of Google search volume covering search terms dating back to 2004. The portal does not report the absolute number of searches but rather a *Search Volume Index* (SVI) ranging from 1-100 based on the relative popularity of a search term in the specified region and period. The resulting SVI time series is normalised for a given search term and period, with 100 representing the maximum user interest across the window.

I obtain the SVI for stock tickers of all remaining firm-event observations in the sample, excluding firms whose stock ticker changed during the estimation window or the event window of [-15;+15] trading days. Ticker search data is gathered at a weekly frequency for the region of the US, as US stock markets are the focus of my study. The final search period for each ESG scandal covers eleven months before and two months after the event date (55-56 weeks total). To automate Google Trends requests, I use the R-package *trendecon* developed by Eichenauer et al. (2022).

As Google Trends does not access the entire population of search requests but only a representative sample, observations with low search volume appear as 0. A high proportion of zeros indicates low overall interest in the specified search term, leading to extreme sampling variation and affecting subsequent results (Eichenauer et al. (2022)). Therefore, to include only tickers with meaningful SVI, I require that the number of zeros in each SVI time series be below six or 11% of total observations. This restriction leaves a sample of 1,465 valid SVI time series around as many ESG incidents.

Finally, to address the question of whether investor attention can predict the extent of abnormal returns around ESG incidents, I construct a measure of attention shocks using the methodology of Da et al.

(2011). This measure is referred to as *Abnormal Search Volume Index* (*ASVI*) and is defined as log of the ratio of SVI in the event week to the median of SVI over the previous eight weeks.

4. Empirical Results

4.1. Event returns of ESG scandals

In the first part of the empirical analysis, I conduct an event study around large jumps in RRI, as previously done by Glossner (2021). I aim to reproduce prior results and to provide the basis for analysing the predictive power of retail investor attention for abnormal returns. My event study follows the methodology laid out by MacKinlay (1997) and largely uses the same parameters and data as Glossner (2021), though the sample in my study is slightly larger and spans to August 2020 instead of December 2017.

First, I estimate normal returns for all 2,156 events in the sample by applying the market and four-factor Carhart (1997) models in an estimation window ranging from 299 to 50 trading days before the event trading day. Returns of the risk-free rate and the four risk factors are obtained from Kenneth French's website (French (2023)). Then, I calculate CARs for event windows covering 21 or 31 days around the event trading day. Departing from the parameters of Glossner (2021), I additionally estimate CARs for extended windows after the event trading day, specifically from day 1 up to days 60 and 120. This allows for the observation of drift in abnormal returns after the initial impact of the event. I report the results of this event study in Table 1. Here, CARs are shown for the full sample of ESG incidents and for two subsamples with an RRI Trend of at least 30 and 40, respectively.

In the narrow 21- and 31-day event windows around the ESG scandal, I find negative CARs ranging from 1.6% to 2.4% and with significance at or above the 5% level (outside of one exception in the subsample of largest incidents). In addition, CARs are economically meaningful and become more negative in samples with bigger RRI changes, indicating more serious events. The notion of more severe events in terms of RRI Trend (Glossner (2021)) or more negatively worded CSR news (Krüger (2015)) causing stronger investor reactions is in line with previous event studies of ESG news. Generally, my results are similar in extent to those reported in the analogous event study by Glossner (2021). However, I observe CARs lower by 4% to 40%, especially in the subsample of RRI Trend >=40. Finally, no notable differences appear in the results between the two risk models.

Complementing the tabulated results, Figure 1 graphically displays the discussed CARs spanning 15 days before until 120 after the event trading day. Here, I find that CARs observed within the 21- and 31-day event windows are almost entirely realised before the event day. Accordingly, these abnormal returns indicate a market reaction prior to the publication of ESG incident news. An alternative hypothesis is that the event dates are misidentified, with negative ESG episodes for firms in the sample starting earlier than suggested by the chosen event date. However, only around 1% of ESG scandals in the sample were preceded by other ESG incident news days for the same company in the 25 calendar days leading up to the event. Therefore, it is likely that a large part of the market reaction to ESG scandals indeed tends to occur before their publication in the news or other media.

As outlined in the previous section, my study relies on weekly SVI to measure investor attention and uses event-week abnormal attention as a predictor. The realisation of abnormal losses *before* the event suggests the need to study investor attention in the days leading up to the ESG scandal. This may be done using higher frequency (i.e., daily) Google search volume data, which could be part of future research surrounding this topic.

In the extended event windows ([+1;+60] and [+1;+120] in Table 1), I generally observe insignificant results for CARs. However, CARs show significance at the 10% level and above in the subsample of the largest scandals (RRI Trend >=40), where abnormal losses are also economically meaningful at more than 3%. Further, as visible in the graphical display of CARs in Figure 1, CARs stay flat or revert slightly from the event day until day 15. After this point, further abnormal returns are entirely realised as "delayed" drift, which is distinguishable from the immediate reaction around the event.

The particularly strong drift for the largest scandals (measured by RRI Trend) may suggest that more serious ESG incidents are followed by additional negative abnormal returns. This finding agrees with studies conducted by Glossner (2021), who shows that stocks with elevated 2-year peak RRI and current RRI exhibit significant negative abnormal returns in out-of-sample tests. He also finds an investor tendency to underreact to negative ESG information. Accordingly, the drift following the narrow event window [-15;+15] may represent the correction to an initial underreaction. For instance, Glossner (2021) shows that analysts underestimate the impact of negative ESG incidents on companies and consequently are negatively surprised in subsequent earnings announcements. However, the study considers analyst earnings surprises at a one-year horizon, whereas the abnormal returns in the extended window of this study start much earlier, beginning around one month past the event (15 trading days). In the next section of this study, I introduce retail investor attention as a predictor of abnormal returns and comment further on possible explanations of this drift.

4.2. ASVI as a predictor of abnormal returns around ESG scandals

Next, I examine whether the level of individual investor attention during an ESG scandal can predict the extent of abnormal returns around the incident. I explore this question by using the previously determined event week ASVI, resulting from ticker searches in Google. The regression I run is of the form:

$CAR[t_1;t_2]_i = \alpha + \beta_1 * Event\ week\ ASVI$, where $CAR[t_1;t_2]_i$ denotes the CAR of ESG scandal i from day t_1 until t_2, relative to the event day. The results of this regression are visible in Table 2.

For CARs in the narrow event windows of [-10;+10] and [-15;+15], I find significantly negative coefficients for ASVI, although only at the 10% significance level in the sample covering all events. The significance of the coefficients tends to increase with the minimum jump in RRI included in the respective subsample, and it is strongest for scandals with RRI Trend >= 40. This indicates investor attention has a stronger influence on CAR in a sample of more serious ESG scandals. In addition, the results are also economically significant. As an example, when considering events with an RRI Trend >=30 in the market model, the ASVI coefficient of -3.104 indicates a reduction in

CAR[-10;10] by 2.15% if the SVI during the event week doubles in comparison to the median SVI of the previous eight weeks.

Notably, the abnormal returns around the ESG incidents in this study occur primarily *before* the event day (t=0) and therefore precede the attention measure of event week ASVI. Consequently, the coefficients I find for ASVI in the narrow event windows (21- and 31-day) are not free from reverse causality concerns. For instance, high event week ASVI may be caused by previously realised abnormal returns. Alternatively, another variable, such as the seriousness of the ESG incident (quantified by RRI Trend), could be driving both attention and abnormal returns. I address some of these robustness concerns in the next section.

On the other hand, the concerns mentioned are less salient for the results of post-event drift measured in the windows [+1;+60] and [+1;+120], which are also shown in Table 2. I find statistically and economically significant negative coefficients for ASVI in many subsamples, which suggests that greater attention at t=0 measured through Google search volume predicts post-event drift in the weeks and months following the ESG scandal.

The drift pattern seen in Figure 1 resembles an underreaction, as documented in the case of earnings announcements by Bernard and Thomas (1989)). This is seemingly at odds with the finding that higher SVI during the event week predicts higher post-event drift. As documented by Hou et al. (2009), greater attention on the event should typically reduce subsequent drift, as more relevant information is incorporated into prices on the event day. Some of this seeming disagreement with my results can be explained by the type of attention studied here. For instance, Ben-Rephael et al. (2017) argue that retail investor attention primarily captured by Google does not significantly contribute to information corporation on the event day, unlike institutional investor attention. Still, an underreaction story is unlikely to fully account for the observed drift for multiple reasons.

First, while Ben-Rephael et al. (2017) find that higher SVI does not alleviate drift following earnings announcements, they also do not present clear evidence of it exacerbating drift beyond the first 5 days after the event. This is in stark contrast to my results, where I find strong predictive power of ASVI for post-event drift. Second, previous studies have demonstrated that company value is negatively affected when high public awareness is combined with a poor reputation for ESG practice (Servaes and Tamayo (2013)). As outlined in the introductory section, subsequent losses in firm value after the ESG scandal could therefore result from an investor or consumer response to the scandal, producing additional negative news. Partially, this argument relies on ticker searches in Google not only capturing retail investor attention but also proxying for consumer attention. This could be examined in subsequent research. Overall, while potential explanations of underreaction cannot be entirely dismissed, the strength of ASVI as a predictor of drift suggests that an explanation related to individual investor or consumer behaviour is more likely to account for the return patterns observed around ESG scandals.

4.3. Robustness of ASVI as a predictor of abnormal returns

In this section, I re-run the previous regression of CARs on ASVI under the inclusion of additional control variables to test the robustness of my results. First, I examine whether the seriousness of the ESG scandal, measured by RRI Trend, is an important predictor of CARs and if the significance of event week ASVI persists when including it. Accordingly, the regression for this test is of the following form:

$CAR[t_1;t_2]_i = \alpha + \beta_1 * Event\ week\ ASVI_i + \beta_2 * RRI\ Trend_i$, whereby RRI Trend refers to the one-month increase in current RRI caused by the ESG scandal. Results for this regression are presented in Table 3 and strongly resemble those found in the previous regression, with ASVI as the sole predictor. I find that including RRI Trend has little effect on the extent and significance of the coefficients for my attention measure. Importantly, event week ASVI also largely retains the same predictive power as in the base case for post-event drift observed in the [+1;+60] and [+1;+120] windows.

At the same time, I find that RRI Trend does not perform well as a predictor. Consistent with intuition, regression coefficients for this variable are negative, implying larger losses for ESG scandals categorised as more serious by RepRisk. However, the coefficients are mostly insignificant outside of the subsample of the largest scandals (RRI Trend >=40), where RRI Trend is a significant predictor for abnormal losses in the [-15;+15] window. This may suggest that investors are more sensitive to the nuances of information in ESG scandals as the incidents become more serious.

In a second robustness exercise, I examine whether abnormal returns leading up to the event and on the event day are a better predictor for subsequent drift and fully explain the significance of event week ASVI. The phenomenon of large abnormal event returns predicting future drift was previously demonstrated by Chan et al. (1996) in their study of underreaction as a cause for momentum anomalies. Consequently, I add CAR[-15;0] as an explanatory variable to the previous regression and focus exclusively on post-event drift as the dependent variable.

Table 4 displays the results of this regression. I find that coefficients and t-statistics of ASVI are materially lower in this test. Nevertheless, the coefficients remain economically meaningful and statistically significant in many subsamples, including for post-event drift in a 60-day window observed in the sample containing all events. Further, I find that CAR[-15;0] performs better as a predictor of post-event drift than RRI Trend. The predictive power of abnormal returns around the event for future drift aligns with the results of Chan et al. (1996), who find a similar pattern for earnings announcements.

Overall, the results suggest that retail investor attention significantly correlates with abnormal losses in 21- and 31-day symmetric windows around ESG scandals. However, reverse causality concerns remain around its predictive power for event returns and require further study of daily attention leading up to the event. The results also indicate that ASVI, as measured in this study, is a significant predictor for post-event drift following ESG incident news, which is robust to the inclusion of control variables such as (pre-)event returns and the seriousness of the scandal in question.

5. Conclusion

In this study, I confirm previous findings showing losses in firm value during ESG scandals. I further find that most of these losses are realised before the news about the ESG incident is first published and that the most serious scandals are followed by significant post-event drift. I study retail investor attention to these incidents and document significant coefficients in cross-sectional regressions of abnormal event returns on my attention measure. These significant coefficients appear both for returns realised directly around the event and for post-event drift measured after.

Two conclusions emerge from this analysis: First, the predictive power of individual investor attention on event returns is still in question, as these returns are largely realised before the event while my attention measure is set during the event week. Future studies may employ daily Google search data to examine how attention behaves in the days leading up to the publication of news about the ESG scandal. Second, retail attention appears to have predictive power for post-event drift, and the strength of the prediction tends to increase in samples of more serious scandals. This finding is also robust when controlling for the seriousness of the scandal and for returns realised prior to the drift. Unlike typical underreaction explanations, where greater attention alleviates drift, the opposite appears to be true for retail investor attention and ESG scandals. This points to delayed reactions to ESG scandals, which are not apparent on the event day. These reactions could involve selling pressure from retail investors or consumer action such as product boycotts. Future studies may focus on the precise channel through which firm value is affected in these scandals. Therefore, a question of future research could be whether abnormal losses around ESG scandals are caused by rational reactions to fundamental changes or, indeed, by socially responsible behaviour from investors and consumers, which is not initially “justified” by fundamentals.

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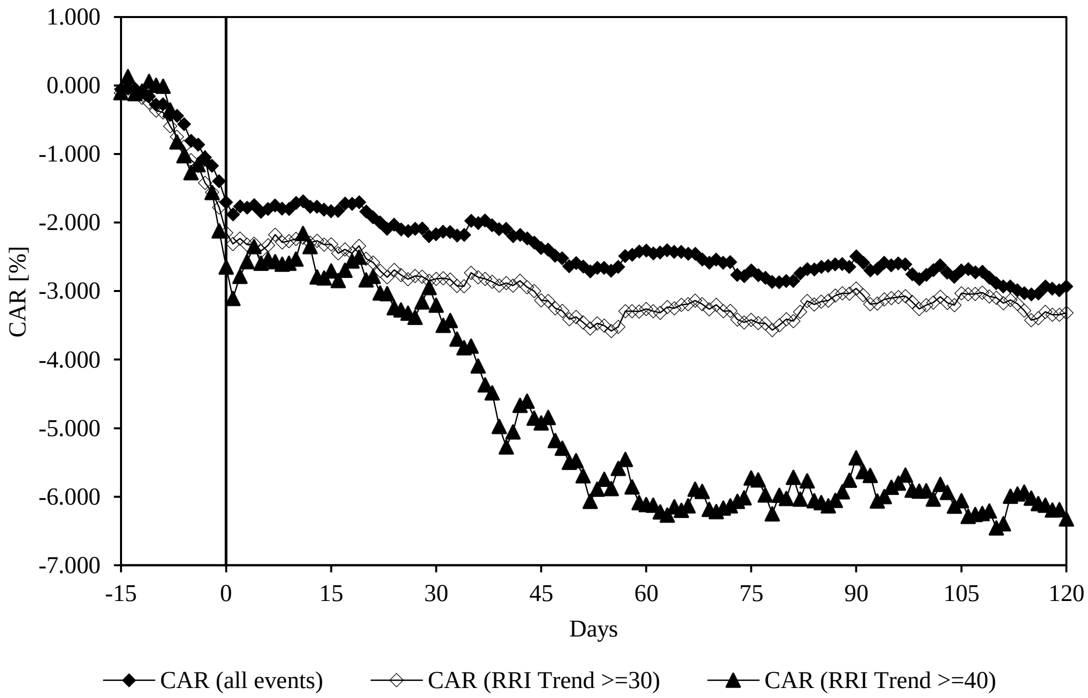
Figure 1: Plot of cumulative abnormal returns for ESG incidents

This chart plots the cumulative abnormal returns around ESG risk incidents from event day -15 up to event day 120. Panel A calculates abnormal returns using the market model, while Panel B uses the Carhart (1997) four-factor model.

Panel A: Market model



Panel B: Four-factor model

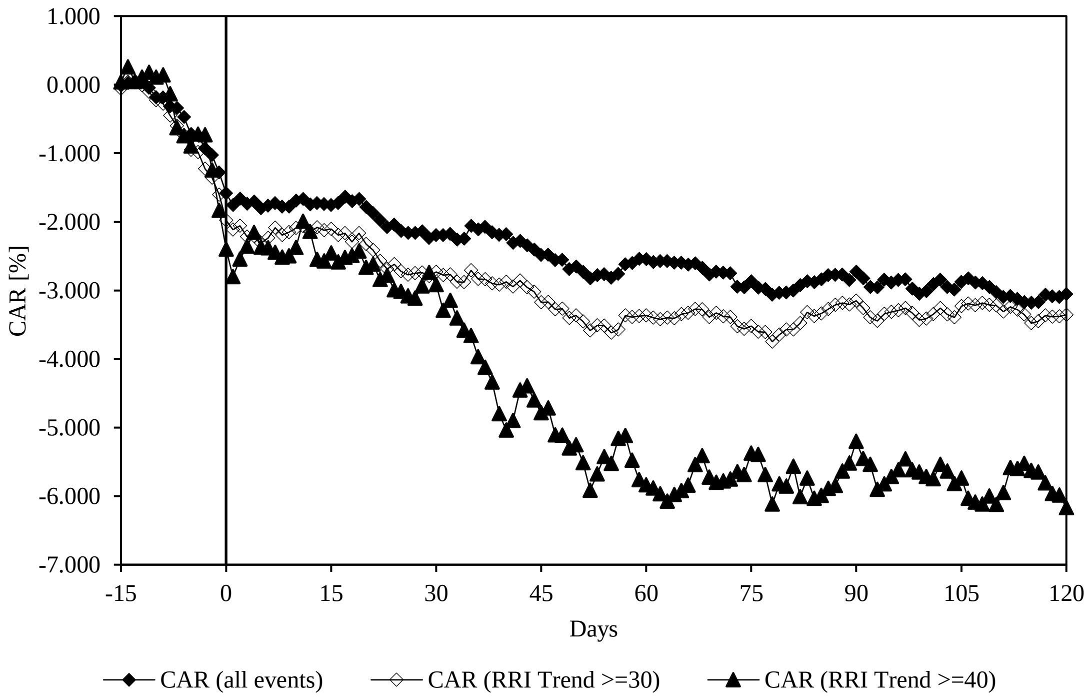


Table 1: Event returns of ESG incidents

This table presents the results of event studies around ESG risk incidents. Events are identified as an increase in RRI of at least 25, though the minimum RRI in the final sample with complete daily return data is 26. I determine the exact event date by finding the date of the first ESG incident news registered by RepRisk for each firm-month observation. The columns indicate the minimum RRI increase in the respective subsample (RRI Trend), the length of the event window in trading days (Window), the number of events in the subsample (Events), the observed CAR in the specified event window (CAR) and the associated t-statistic (t-stat). Panel A estimates normal returns using the market model, while Panel B uses the four-factor Carhart (1997) model. All events took place between January 2007 and August 2020. *, ** and *** mark the respective significance levels of 10%, 5% and 1%.

Panel A: Market model

RRI Trend	Window	Events	CAR	t-stat
>=26	[-10;+10]	2,156	-1.612***	-4.61
>=26	[-15;+15]	2,156	-1.806***	-4.30
>=26	[+1;+60]	2,135	-0.752	-1.36
>=26	[+1;+120]	2,097	-1.231	-1.47
>=30	[-10;+10]	1,574	-2.014***	-5.06
>=30	[-15;+15]	1,574	-2.204***	-4.60
>=30	[+1;+60]	1,560	-1.082*	-1.69
>=30	[+1;+120]	1,533	-1.166	-1.21
>=40	[-10;+10]	253	-2.312**	-2.30
>=40	[-15;+15]	253	-2.394**	-2.20
>=40	[+1;+60]	252	-3.556**	-2.52
>=40	[+1;+120]	248	-3.674*	-1.88

Panel B: Four-factor model

RRI Trend	Window	Events	CAR	t-stat
>=26	[-10;+10]	2,156	-1.629***	-4.74
>=26	[-15;+15]	2,156	-1.660***	-3.97
>=26	[+1;+60]	2,135	-0.956*	-1.74
>=26	[+1;+120]	2,097	-1.469*	-1.78
>=30	[-10;+10]	1,574	-1.956***	-5.03
>=30	[-15;+15]	1,574	-1.922***	-4.05
>=30	[+1;+60]	1,560	-1.286**	-2.03
>=30	[+1;+120]	1,533	-1.378	-1.46
>=40	[-10;+10]	253	-2.181**	-2.32
>=40	[-15;+15]	253	-2.054*	-1.96
>=40	[+1;+60]	252	-3.625***	-2.80
>=40	[+1;+120]	248	-3.769**	-2.05

Table 2: Event returns predicted by event week ticker ASVI

This table regresses CARs calculated in different subsamples and event windows on event week ticker ASVI. Panel A presents results for CARs estimated using the market model, and panel B using the four-factor Carhart (1997) model. t-statistics are reported in brackets. *, ** and *** mark the respective significance levels of 10%, 5% and 1%.

Panel A: Market model

Sample	All events				RRI Trend >=30				RRI Trend >=40			
Window	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]
Intercept	-1.339***	-1.170**	-0.468	-1.287	-1.717***	-1.554***	-0.659	-0.667	-2.117*	-2.294*	-3.016**	-5.365***
(t-stat)	(-3.18)	(-2.31)	(-0.73)	(-1.29)	(-3.61)	(-2.69)	(-0.86)	(-0.57)	(-1.76)	(-1.89)	(-2.35)	(-2.69)
Event week ASVI	-1.872*	-2.590*	-2.997**	-4.407*	-3.104**	-4.311***	-3.324**	-4.953*	-6.091**	-8.029**	-6.540*	-11.715**
(t-stat)	(-1.73)	(-1.94)	(-2.25)	(-1.93)	(-2.41)	(-2.66)	(-2.04)	(-1.73)	(-2.38)	(-2.30)	(-1.90)	(-2.42)
Observations	1,465	1,465	1,454	1,434	1,069	1,069	1,061	1,048	170	170	170	170
Adjusted R^2	0.0019	0.0027	0.0021	0.0018	0.0065	0.0087	0.0024	0.0022	0.0425	0.0721	0.0404	0.0557

Panel B: Four-factor model

Sample	All events				RRI Trend >=30				RRI Trend >=40			
Window	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]
Intercept	-1.332***	-0.983**	-0.558	-1.169	-1.621***	-1.230**	-0.743	-0.523	-2.184**	-2.101*	-2.436*	-4.688**
(t-stat)	(-3.22)	(-1.96)	(-0.87)	(-1.19)	(-3.48)	(-2.16)	(-0.98)	(-0.46)	(-2.02)	(-1.83)	(-1.91)	(-2.26)
Event week ASVI	-1.723*	-2.311*	-2.640**	-3.798*	-2.578*	-3.597**	-2.270	-3.509	-5.785**	-6.973**	-5.417**	-9.643***
(t-stat)	(-1.54)	(-1.794)	(-2.16)	(-1.84)	(-1.89)	(-2.18)	(-1.55)	(-1.41)	(-2.20)	(-2.14)	(-2.34)	(-3.65)
Observations	1,465	1,465	1,454	1,434	1,069	1,069	1,061	1,048	170	170	170	170
Adjusted R^2	0.0016	0.0021	0.0015	0.0013	0.0044	0.0060	0.0007	0.0007	0.0474	0.0600	0.0274	0.0340

Table 3: Robustness check - event returns predicted by event week ticker ASVI and RRI Trend

This table regresses CARs on both event week ticker ASVI as well as the one-month increase in current RRI caused by the ESG scandal. Panel A presents results for CARs estimated using the market model, and panel B using the four-factor Carhart (1997) model. t-statistics are reported in brackets. *, ** and *** mark the respective significance levels of 10%, 5% and 1%.

Panel A: Market model

Sample	All events				RRI Trend >=30				RRI Trend >=40			
Window	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]
Intercept	3.704	3.936	2.890	1.129	2.654	3.000	4.041	11.966	31.255*	33.796**	-0.309	8.889
(t-stat)	(1.20)	(1.16)	(0.75)	(0.19)	(0.66)	(0.70)	(0.84)	(1.60)	(1.86)	(2.24)	(-0.02)	(0.42)
Event week ASVI	-1.929*	-2.648**	-3.034**	-4.437*	-3.141**	-4.350***	-3.362**	-5.067*	-6.711***	-8.699***	-6.590*	-11.980**
(t-stat)	(-1.78)	(-1.98)	(-2.28)	(-1.94)	(-2.44)	(-2.68)	(-2.06)	(-1.75)	(-2.99)	(-2.87)	(-1.91)	(-2.57)
RRI Trend	-0.155*	-0.157	-0.103	-0.074	-0.127	-0.132	-0.137	-0.367*	-0.794*	-0.859**	-0.064	-0.339
(t-stat)	(-1.65)	(-1.51)	(-0.88)	(-0.42)	(-1.07)	(-1.05)	(-0.99)	(-1.74)	(-1.95)	(-2.37)	(-0.18)	(-0.71)
Observations	1,465	1,465	1,454	1,434	1,069	1,069	1,061	1,048	170	170	170	170
Adjusted R^2	0.0033	0.0035	0.0019	0.0012	0.0067	0.0086	0.0020	0.0029	0.0663	0.0987	0.0348	0.0519

Panel B: Four-factor model

Sample	All events				RRI Trend >=30				RRI Trend >=40			
Window	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]	[-10;+10]	[-15;+15]	[+1;+60]	[+1;+120]
Intercept	3.235	3.390	1.831	-0.144	3.038	3.763	2.156	10.211	30.403*	32.947**	-7.338	-9.662
(t-stat)	(1.08)	(1.00)	(0.48)	(-0.02)	(0.78)	(0.88)	(0.45)	(1.38)	(1.87)	(2.20)	(-0.51)	(-0.48)
Event week ASVI	-1.775	-2.361*	-2.667**	-3.811*	-2.618*	-3.639**	-2.294	-3.606	-6.391***	-7.624***	-5.326**	-9.550***
(t-stat)	(-1.58)	(-1.77)	(-2.18)	(-1.84)	(-1.91)	(-2.19)	(-1.57)	(-1.43)	(-2.79)	(-2.69)	(-2.22)	(-3.57)
RRI Trend	-0.141	-0.135	-0.074	-0.032	-0.136	-0.145	-0.084	-0.312	-0.776*	-0.834**	0.117	0.118
(t-stat)	(-1.55)	(-1.30)	(-0.64)	(-0.18)	(-1.20)	(-1.17)	(-0.61)	(-1.50)	(-1.96)	(-2.30)	(0.34)	(0.26)
Observations	1,465	1,465	1,454	1,434	1,069	1,069	1,061	1,048	170	170	170	170
Adjusted R^2	0.0027	0.0025	0.0011	0.0006	0.0049	0.0062	-0.0001	0.0010	0.0761	0.0884	0.0222	0.0284

Table 4: Robustness check – regression of post-event drift

This table regresses post-event drift, i.e., CARs after t=1, on event week ticker ASVI and RRI Trend, and introduces CARs in the period [-15;0] as an additional control variable. Panel A of the table presents results for CARs estimated using the market model, and Panel B using the four-factor Carhart (1997) model. t-statistics are reported in brackets. *, ** and *** mark the respective significance levels of 10%, 5% and 1%.

Panel A: Market model

Sample	All events		RRI Trend >=30		RRI Trend >=40	
Window	[+1;+60]	[+1;+120]	[+1;+60]	[+1;+120]	[+1;+60]	[+1;+120]
Intercept	2.541	0.066	3.923	11.581	-7.048	-2.861
(t-stat)	(0.67)	(0.01)	(0.82)	(1.57)	(-0.48)	(-0.14)
Event week ASVI	-2.848**	-4.197*	-3.159*	-4.689*	-4.889*	-9.015**
(t-stat)	(-2.17)	(-1.89)	(-1.93)	(-1.67)	(-1.66)	(-2.38)
RRI Trend	-0.089	-0.030	-0.130	-0.346*	0.111	-0.034
(t-stat)	(-0.76)	(-0.17)	(-0.95)	(-1.67)	(0.32)	(-0.07)
CAR [-15;0]	0.103	0.300**	0.063	0.198	0.301***	0.524**
(t-stat)	(0.97)	(2.27)	(0.46)	(1.11)	(3.43)	(2.43)
Observations	1,454	1,434	1,061	1,048	170	170
Adjusted R^2	0.0055	0.0147	0.0024	0.0071	0.0948	0.1292

Panel B: Four-factor model

Sample	All events		RRI Trend >=30		RRI Trend >=40	
Window	[+1;+60]	[+1;+120]	[+1;+60]	[+1;+120]	[+1;+60]	[+1;+120]
Intercept	1.498	-1.305	2.037	9.751	-13.499	-21.072
(t-stat)	(0.40)	(-0.23)	(0.42)	(1.33)	(-0.93)	(-0.98)
Event week ASVI	-2.513**	-3.584*	-2.177	-3.364	-4.167**	-7.405***
(t-stat)	(-2.06)	(-1.77)	(-1.47)	(-1.36)	(-1.99)	(-3.32)
RRI Trend	-0.060	0.014	-0.079	-0.292	0.274	0.410
(t-stat)	(-0.53)	(0.08)	(-0.58)	(-1.41)	(0.80)	(0.83)
CAR [-15;0]	0.084	0.285**	0.041	0.158	0.237***	0.439**
(t-stat)	(0.72)	(2.06)	(0.27)	(0.88)	(2.96)	(2.01)
Observations	1,454	1,434	1,061	1,048	170	170
Adjusted R^2	0.0031	0.0124	-0.0005	0.0034	0.0555	0.0734