Do sustainable company stock prices increase with ESG scrutiny? Evidence using social media

Emilie Kvam, Peter Molnár, Ingvild Wankel and Bernt Arne Ødegaard*

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Abstract

We study the links between short-term stock returns and ESG (Environmental, Social and Governance) concerns. The ESG concerns are measured by ESG-related sentiment extracted from Google Trends and Twitter. Companies with high ESG scores deliver high short-term returns in times of heightened ESG concerns, measured both using heightened social media interest in ESG (at the company or economy-wide level), and increased economic uncertainty (measured by the VIX index). Our results are consistent with Cornell (2020)'s arguments of increased short-term demand for high-quality ESG stocks at times when ESG concerns come to the forefront. On average stock returns are decreasing in ESG rankings, consistent with the implications of equilibrium models of Pastor et al. (2021) and Pedersen et al. (2021).

Keywords: ESG (Environmental, Social, Governance) concerns; Social Media; Stock Returns
JEL codes: G10; G12

Introduction

For investors, ESG (environmental, social and governance) concerns has in recent years moved to the forefront. Institutional investors maintain lists of companies excluded for ESG reasons, and the popularity of "responsible" mutual funds is growing apace.[1] The key research questions driven by this "ESG investment revolution" concerns the equilibrium consequences for stock prices. When a large fraction of investors rule out the stocks of "bad" (in the ESG sense)

*Kvam and Wankel from the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. Molnár from the Norwegian University of Science and Technology and University of Stavanger (UiS), Stavanger, Norway. Ødegaard from the University of aStavanger. Corresponding author: Bernt Arne Ødegaard. Email: bernt.a.odegaard@uis.no. Postal adress: UiS Business School, EOJ Building, University of Stavanger, NO-4036 Stavanger, Norway. Declaration of Interest: none.

[1]See recent surveys of the academic literature in Coqueret (2021) and Liang and Renneboog (2020).

companies from their investable universe, will these demand changes move the relative pricing of the "good" stocks versus the "bad"? In what directions? These questions are asked in the context of theoretical models by e.g. Pástor et al. (2021) and Pedersen et al. (2021), who build models where a subset of investors has preferences in "ESG dimensions" in addition to asset returns. For example, the Pástor et al. (2021) model has a clear prediction: With a subset of investors with "ESG preferences," stocks with high ESG scores can sustain a lower asset return, as these investors are willing to forgo asset returns in lieu of the higher utility from owning "responsible" equities.

Our analysis complements this analysis by looking at short-term movements in stock prices, and link the price changes to ESG-related information. By investigating whether stock prices react to shocks in public information, which we measure using social media, we can shed light on questions such as: When companies improve their ESG score, by for example increasing their sustainable credentials, or when there is a preference shift among investors, how will stock prices of high-quality ESG stocks react? Will an increased demand for "Green" stocks push these prices up?

Specifically, we investigate short term (daily and weekly) US stock returns and use data from social media to identify periods with intense (economy- or company-level) focus on ESG. Our findings can be summarized as follows.

Incorporating short-term data from social media, we interact company-level measures (from Google search data) of firm interest with company ESG measures. Here we find that high-quality ESG firms have superior returns in periods with heightened scrutiny of the company. These company-level results are consistent with price increases on positive ESG news.

As an alternative take on the social media data, we look at economy-wide variations in ESG concerns. We measure the degree of social media ESG concerns using data from Google and Twitter. These are periods where investors preferences are likely to change. For example, when climate-concerns increase, people care more about the carbon footprint of companies. We find that high-quality ESG firms have higher returns in periods of pessimism in the market (ie. a low Twitter mood on ESG).

In our final set of analyses we ask to what degree the ESG concerns we measure using social media are different from a more general measure of uncertainty in the economy, proxied by the VIX index. This more general measure is motivated by how, during financial crises the hedging properties of "good" (in the ESG sense) companies comes to the forefront.[2] Our results using

[2]This type of implications was crash-tested using the onset of the Covid pandemic in e.g. Albuquerque et al. (2020) and Pástor and Vorsatz (2020), who showed that superior ESG stocks and funds performed relatively better. But there is also similar evidence from the 2008 financial crisis (Lins et al., 2017).

these more general measures complements our results above. We find that the resiliency of high ESG ranked firms goes beyond the major crises mentioned. It is rather a general feature of episodes of high economy-wide volatility.

Let us finally mention that we also regressed short-term stock returns on measures of ESG quality alone (the "level" of ESG quality), and found a negative relationship between stock returns and general ESG quality (i.e. lower returns on "good" ESG firms). This is a confirmation of the large empirical literature showing a negative link between ESG rankings and expected returns. This result is also consistent with theoretical models such as Pástor et al. (2021).

The rest of this study is structured as follows. We first, in section 1, provide background and place our investigations relative to similar research. In section 2 we explain our methods and present the data. Section 3 provides the results, before we offer a short conclusion.

1 Research issue

The broad umbrella of "sustainability concerns" may be a good way to characterize recent trends in society, concerns which have spread to financial markets. In the investment community the early term "Socially Responsible Investing" has been replaced with the current concern with "ESG-aware investing." Mutual funds marketed as "socially responsible" and "sustainable" has seen large inflows, to the extent that today, one third of U.S. assets under management is subject to a sustainable investment strategy (SIF, 2020). Regulation is following practice, the best known is probably the recent EU taxonomy for sustainable activities. This regulation is particularly suited to support the most common strategy for institutional investors, *exclusion*.

This practitioner interest has been followed by academic investigations. Most of the academic work is empirical, looking for links between ESG characteristics and company performance. This literature has grown so quickly that a recent survey (Coqueret, 2021) lists 10 *meta* studies of the issue, the last of which (Whelan et al., 2021) surveyed over 1,000 studies produced in the period 2015–2020. There is no clear conclusion from these studies. While there are many claims of firms "doing well by doing good," there is a substantial portion of this literature that finds that better ESG firms have lower returns. A number of studies investigates the link between firms costs of capital and ESG (El Ghoul et al., 2011; Chava, 2014; Ng and Rezaee, 2015; Breuer et al., 2018), and find evidence that high ranked ESG firms have lower costs of capital (and hence lower expected returns). There are also evidence that firms typically excluded by institutional investors due to "bad" ESG have a return premium (Hong and Kacperczyk, 2009; Berle et al., 2022).

A potential cause of this lack of agreement is the *measurement problem*. ESG – environment, social, governance – represent three different aspects of a company operations. From the investors point of view, it is desirable to come up with a single ESG ranking of stocks. To provide such rankings a whole advisory industry has materialized, with each advisor developing a distinct system of ESG scoring, choosing a set of measurements, which are weighted into numerical representations of ESG scores. Given the large number of choices involved in such procedures, it is no surprise that these scores disagree across providers.[3]

Summarizing the three aspects of ESG into one measure may however be problematic. Arguably, the relevant horizons for the G(overnance) part (incentive type of issues) may be shorter than for the E(nvironment) and S(ocial) issues, for which long term sustainability is more clearly relevant (Drei et al., 2019; Giese et al., 2021). Thus, to assess the risks of sustainable investments, considering each factor separately may be necessary.

Much of the empirical work on ESG does not really discuss why the focus on ESG, and the removal of part of a stock's potential investors through exclusion, should induce differences in expected returns. Intuitively, exclusions should reduce the feasible set of investment portfolios, worsening the risk/return trade-off. We are however seeing an emergent theoretical literature on the equilibrium consequences of ESG concerns (Pástor et al., 2021; Pedersen et al., 2021; Zerbib, 2022). Key to these models is that investors have preferences over both the monetary return from an investment, and the investments' ESG characteristics. For example, investors can feel satisfaction in not supporting gun violence through ownership of gun manufacturers (negative screening). On the other hand, investors may want to support clean energy generation, and get an extra utility from investing in such energy companies.

We have already mentioned the key implication of these models, that they support differences in expected returns depending on the ESG characteristics of company. Pástor et al. (2021) argues that expected returns is decreasing in ESG quality. The model of Pedersen et al. (2021) has similar implications, but less clear cut predictions, as the equilibrium depend on the relative proportions of different types of investors, and one can end up with both higher and lower expected returns for high quality ESG stocks. We term this a "ESG level" effect.

The above theories are essentially static, the proportions of investors of various types are exogenous. In our work we are however concerned with dynamic aspects of ESG concerns. Are

[3]See Berg et al. (2022),Christensen et al. (2021) and Dimson et al. (2020) for discussions of the general measurement problem. Berg et al. (2021) provides some evidence that aggregating across ESG providers can reduce noise, and find that after such a procedure the evidence for a link between ESG and returns is strengthened. Avramov et al. (2022) argues that uncertainty about ESG is a separate source of (priced) risk. Lioui and Tarelli (2022) contains similar results.

times when ESG concerns "rise to the surface" associated with short term stock price reactions? Did for example the media attention during the '21 Glasgow meeting on Climate Change induce changes in people's preferences for investments in clean energy and similar attempts to reach the 2% temperature target? When Siemens in 2021 divested their oil and gas division, the "new" Siemens suddenly was a more climate-friendly corporation. How do investors react? We term such short term effects the result of "ESG concerns."

In the context of the static models above, ESG concerns can be viewed as changes to investor preferences, and therefore the utility function. The expected effect of an improvement in ESG for a given firm is an increase in demand for that stock by investors valuing ESG properties, leading to a short-term price increase (which will lower long term expected returns if the firm's expected cash flows do not change). This type of argument is made by Cornell (2021), who views high returns for ESG firms as a transitory phenomenon due to changing preferences.

There are other theoretical analyses relevant for short term stock price reactions to ESG issues. Avramov et al. (2022) argues that uncertainty about ESG is a separate source of (priced) risk. Implied in their analysis is that the *precision* of the ESG score matter. This is actually key to our investigations. We look at times with increased ESG attention.

In our analysis we look at short term (daily or weekly) stock returns, and relate them to a measure of ESG level (the Refinitiv ESG score), and a measure of ESG attention (ESG concerns). To measure time varying ESG concerns, we primarily use data from Social media, i.e. Google Search and Twitter. We also use the VIX "fear" index as a measure of market-wide investor concerns.

Before moving on to our results, let us discuss how our research relates to other similar studies. The distinguishing part of our research is the use of social media to identify time variation in ESG concerns. The research linking short-term returns, ESG, and social media is limited. Chen et al. (2020) also consider time-variation in social media mentions of ESG, but unlike our research their focus is on the long-term differences in expected returns. They estimate a stock-level ESG-beta using the stocks return history and economy-wide ESG concerns. Thus, as these betas corresponds to systematic risk, their analysis is an attempt to explain differences in expected returns, and their interpretation of such differences is differences in risk.

Ballinari and Mahmoud (2022) construct measures of sentiment for sustainability from social media and link it to short-term stocck returns, but is more concerned with predictability. Ardia et al. (2022) also construct a measure of the degree of climate concerns (not ESG in general) from U.S. newspapers and use it to look at stock price reactions on days of unexpected increase in climate concerns, and find, similarly to our results on more general ESG measures, that firms with good climate credentials see their stock price increase.

Derrien et al. (2021) also uses high-frequency ESG incidents, but link it with revisions to analysts forecast. Unlike our use of social media data directly, Serafeim and Yoon (2021) works with an short-term aggregation of ESG news, TruValueLabs, but does link it with short term stock returns. Their focus is different, though, as it is more concerned with differences in ESG rankings.

Santi (2020) has some similarities with our analysis, she looks at Social Media mentions (StockTwits posts), use it to identify periods of investor concern, and link it to stock returns. We however note that the analysis is specific to climate risks, and that she uses longer term stock returns than our analysis.[4]

Our analysis also links to the literature arguing that high ESG quality stocks may be better hedges in times of crisis, such as the 2008 financial crisis (Lins et al., 2017) and the onset of the Covid pandemic. (Albuquerque et al., 2020; Pástor and Vorsatz, 2020).

2 Methods and Data

We use data for US companies listed at either NYSE or NASDAQ. We regress short term (daily or weekly) stock returns on measures of ESG ranking and ESG concerns, controlling for a number of alternative factors relevant for short-term stock returns. Conceptually, we run estimation of the form:

$$r_{it} = f(\text{ESG level}_{it}, \text{ESG concerns}_{it}, \text{Controls}_{it}),$$

where r_{it} is the stock returns for stock i in period t. We collect stock market data from the Center for Research in Security Prices (CRSP) for the period 2009–2019. In order for a company to be included in the dataset, it must have at least 750 trading days, with a maximum of five consecutive inactive trading days. This requirement reduces our sample from 5,522 to 4,039 companies.

[4] We also acknowledge some more limited analysis with similarities to our analysis. de Groot (2020) and Doldersum (2021) both links Twitter ESG mentions and stock returns, but the analysis is on a more limited sample. Turkson (2021)'s analysis linking VIX to ESG concerns is similar to part of our research, but it does not consider social media. Wong and Zhang (2022) uses an index of corporate ESG reputation, identify periods with negative ESG, and link it with stock returns, but uses monthly returns.

2.1 Company ESG Scores

To measure company ESG rankings we use Refinitiv Eikon scores. While there is a large number of alternative sources of ESG rankings, the Refinitiv ones are widely disseminated, which we view as important when we consider links to social media. We remove companies without ESG data. Our final sample consists of 2030 companies, whereby 1139 are listed on NASDAQ and 891 on NYSE.[5]

The Refinitiv ESG — environmental (E), social (S) and governance (G) — scores are numeric values starting at zero, and increasing in score, with 100 being the maximal achievable. The company ESG score is a combined measure of the E, S and G measures.[6] Table 1 provides some descriptive statistics of the scores. We note that all the scores are positively correlated, but imperfectly so, with the Social (S) and Governance (G) scores the least correlated (0.37).

2.2 Social media data

2.2.1 Google search volume

To measure public attention to companies and ESG topics we employ search volumes on Google, the most used search engine in the world (Statista, 2021). Terms submitted to search engines reflect people's needs, wants, interests and concerns (Ettredge et al., 2005). Therefore, Google search volumes have been studied in a variety of settings.[7] Let us concentrate on those linking social media and stock returns. While Da et al. (2011) and Joseph et al. (2011) find that high Google search volumes predicts higher future returns, Bijl et al. (2016) find that high Google search volumes predicts lower future returns. Chen (2017) finds that more searches for the Dow Jones Industrial Index (DJIA) is related to higher index returns.

Google search volume indices (SVIs) are obtained from Google Trends. The indices represent the relative popularity of a query within a specified time frame and a geographical range. The values lie within a range of 0 to 100, with 100 signifying the maximum search interest. Zero is by Google given to terms with low search volumes.[8]

[5] For a full list of the companies, see the Internet Appendix.

[6] Details on how Refinitiv calculates the scores, and where they obtain the ESG information, can be found in Refinitiv (2021).

[7] For instance, it has been used to estimate the current level of influenza (Carneiro and Mylonakis, 2009; Ginsberg et al., 2009; Pelat et al., 2009), to study public sentiment related to conservation topics (Nghiem et al., 2016), and to forecast consumer behavior (Vosen and Schmidt, 2011; Choi and Varian, 2012).

[8] For a detailed description of how Google estimates the indices, see Google (2021). To create the search volume indices, Google Trends uses a sub-sample of all searches. Consequently, identical queries in Google Trends may produce results that are slightly different (Baker and Fradkin, 2011; Da et al., 2011; Carrière-Swallow and Labbé, 2013; Dietzel, 2016).

Search Volumes on Companies We consider search volumes on company names to capture public attention to individual companies. We use company names, as opposed to tickers, as many tickers are common abbreviations. In addition, the search volumes on tickers are in most cases lower than search volumes on company names.

Minor adjustments are made to the official company names to better capture public interest in the companies. This includes removing "Inc," "International," "Global," "Group" and "Corp." Additionally, words like "energy" and "bank" are added to limit noise in the search queries. We manually validate the relevancy of the search terms based on content and volume.

For searches on company names, we use weekly values due to low daily search volumes. For weekly data, Google Trends limits retrieval to batches of five years. Due to the large number of companies, a different approach than the one used for ESG topics is taken. To obtain data for the entire period for all companies the values are collected in three batches, with one overlapping year between each batch, for each company. We remove the scaling effect of the batches by detrending the data points according to equation (1), where t denotes weeks. If the SVI for a given time period is zero, $\log(SVI_{t,comp})$ is set to zero. The measure is thus calculated as:

$$AbSVI_{t,comp} = \log(SVI_{t,comp}) - \log\left(Median(SVI_{t-1,comp}, SVI_{t-2,comp}, \ldots, SVI_{t-52,comp})\right) \quad (1)$$

Search Volumes on ESG Topics Separate search volume indices on ESG, environmental, social and governance topics are created.[9] The terms are selected based on the metrics within each score formulated by Refinitiv (2021) and the studies of Preis et al. (2013) and Nghiem et al. (2016). We manually validate the relevancy of the search terms based on content and volume.

Search volume indices (SVIs) are constructed for each ESG topic based on the search volumes of the constituting search terms. Google Trends limits the retrieval of daily values to a batch of nine months. Hence, to obtain daily values for the entire time period for each term, we first collect monthly values and then daily values for each month. Further, the daily search volume is weighted based on its monthly value, thus creating comparable daily values for the entire time period in the range 0 to 100. Then, the SVI for each topic is constructed taking the average of all included search term's daily values. Using a similar approach as Da et al. (2011), the SVIs are detrended using equation (2). Here t denotes days. The search volumes over the weekend is included on the first trading day of the following week. If the SVI for a given time

[9] The search terms included in each index can be found in the Internet Appendix.

period is zero, $\log(SVI_t)$ is set to zero.

$$AbSVI_t = \log(SVI_t) - \log\left(Median(SVI_{t-7}, SVI_{t-14}, \ldots, SVI_{t-364})\right) \tag{2}$$

2.2.2 Twitter

Our second source of social media data is Twitter. We proxy for investor attention by the number of Twitter posts (tweets) related to ESG and the content of these. The content is analyzed using sentiment analysis to capture the public mood about ESG. Sentiment analysis studies people's opinions, attitudes and emotions from written language (Nasukawa and Yi, 2003; Liu, 2012; Medhat et al., 2014), and is a popular technique within natural language processing (NLP). A representation of the public sentiment and opinion about current events is social media (Pagolu et al., 2016). One social media service is Twitter; a public micro-blogging platform that allows its users to share opinions and interact with others. Due to the character limit and the informal and specialized language of tweets, sentiment analysis on Twitter is popular among researchers for studying public mood (Go et al., 2009; Agarwal et al., 2011; Kouloumpis et al., 2011; Wang et al., 2012; Severyn and Moschitti, 2015). While there has been studies using Twitter to predict stock returns (Bollen et al., 2011; Mittal and Goel, 2012; Sul et al., 2014; Pagolu et al., 2016) and research on the attitudes towards climate (Cody et al., 2015; Dahal et al., 2019), the two topics have assumingly not yet been studied together.

To implement our measures, public English tweets containing the words "climate change," "corporate governance," "ESG," "social responsibility" or "sustainability" are scraped from Twitter. We exclude the tweets that satisfy either of the following:

- Identical content by the same user on the same day, disregarding hyperlinks. These tweets are usually spam.
- Contains the word "ESG" and either "music," "song," "concert," "album" or "band." These tweets are related to a band called ESG.

This results in a total of 42,087,585 tweets for the period 2009-2019, from 5,591,528 distinct users. 31,058,349 tweets contain the word "climate change," 437,602 contain "corporate governance," 750,574 contain "ESG," 930,463 contain "social responsibility" and 8,910,587 contain "sustainability." A certain amount of tweets, even after pre-processing, might not be related to ESG topics, and some tweets might still be regarded as spam. This creates some unavoidable noise in our dataset.

The volume of tweets, TV, is detrended according to equation (3). The time period, t, is a day, regarded as the time from the previous market close until the current day's close. If there are no tweets for a given time period, $\log(TV_t)$ is set to zero.

$$AbTV_t = \log(TV_t) - \log\left(Median(TV_{t-7}, TV_{t-14}, \ldots, TV_{t-364})\right) \tag{3}$$

This abnormal volume of tweets, AbTV, is employed as a measure of ESG concern. Table 2 presents the correlation between the five keywords' abnormal Twitter volume.

Sentiment Analysis To evaluate public mood, sentiment analysis is performed on the tweets. Before using sentiment analysis, the tweet content is cleaned to improve accuracy. All tweets are therefore stripped from URLs, hashtags (#), mentions (@), retweet indicators (RT) and other symbols.

We use three pre-trained models to categorize each tweet into positive, neutral or negative sentiment. The first two models use a lexicon-based approach, while the third uses a machine learning method.

The first model uses the natural language processing (NLP) package TextBlob, built on the Natural Language Toolkit (NLTK) package in Python. This model, further referred to as TextBlob, analyses the content based on the word pattern in each tweet, and has been trained on movie reviews. TextBlob sets a polarity score in the range highly positive, +1, to highly negative, −1, with zero being neutral. Hasan et al. (2018) and Laksono et al. (2019) find a 76% and 69% accuracy respectively in using TextBlob for Twitter sentiment analysis. According to TextBlob, 38% of our tweets are positive, 44% are neutral and 18% are negative.

The second model is NLTK's VADER, further referred to as VADER. This model also categorizes into positive, neutral or negative sentiment indicated by values between +1 and −1. In addition to using a sentiment lexicon approach, VADER uses grammatical rules and syntactical conventions. The model is by design made for micro-blogging content. Hutto and Gilbert (2014), the creators of VADER, claim to achieve a 96% accuracy. According to VADER, 38% of our tweets are positive, 34% are neutral and 28% are negative.

The third model uses a machine learning based sentiment analyzer called Flair. Flair's sentiment classifier is based on a character-level long-short term memory (LSTM) neural network that takes sequences of letters and words into account when predicting a sentiment. An advantage over the other two models is that Flair can predict a sentiment for words it has never seen before. This model has been trained on 25 thousand highly polarized IMDb reviews and categorizes into positive or negative. The model classifies 58% of our tweets as positive and 42%

as negative.

We base our sentiment analysis on pre-trained models. This results in an uncertain accuracy. To conclude on a sentiment, we choose the most agreed upon polarity by the three models. This is either the sentiment that at least two of the models agree upon, or if all three disagrees, a neutral polarity is set. In Table 3 we present some examples of tweets in our dataset, with the corresponding polarity score by the three models, and the resulting sentiment. The distribution of tweets into the sentiments by each model can be found in Table 4. We observe that the three models agree on the polarity of 24% of the tweets and disagrees on 12%. Thus, in most cases, there is a high agreement on the polarity and presumably a satisfying level of accuracy.

We define $AbTV^+$ and $AbTV^-$ as the abnormal volume of tweets that the sentiment analysis label as positive and negative respectively. These variables are calculated as:

$$AbTV_t^{sentiment} = \log\left(TV_t^{sentiment}\right) - \log\left(Median(TV_{t-7}^{sentiment}, TV_{t-14}^{sentiment}, \ldots, TV_{t-364}^{sentiment})\right) \quad (4)$$

Here *sentiment* represents either positive, +, or negative, −, sentiment, and t indexes date.

We also create a mood index ($MOOD_t$) which combines the amount of tweets per day labeled as positive, neutral and negative to give an indication of the overall mood:

$$MOOD_t = \frac{TV_t^+ - TV_t^-}{TV_t} \quad (5)$$

2.3 Other market data

In the analysis we additionally employ the CBOE Volatility Index (VIX) as a measure of market-wide uncertainty. The VIX is a measure of the implied short-term volatility for the US stock market, calculated from option prices. VIX reflects investor uncertainty and is known as the “investor fear gauge” (Whaley, 2000). VIX spikes during crisis. Such events are also reflected in the stock market, as stock returns are negatively correlated with implied market volatility (French et al., 1987; Sarwar, 2012).

To measure the state of VIX we use the deviation from the previous one year’s median, $AbVIX$:

$$AbVIX_t = \log(VIX_t) - \log\left(Median(VIX_{t-1}, VIX_{t-2}, \ldots, VIX_{t-252})\right) \quad (6)$$

In addition to the VIX, we consider a number of additional controls. Previous research find that trading volume is significant in explaining stock returns (Campbell et al., 1993; Conrad et al., 1994; Chordia and Swaminathan, 2000). Using a similar approach to Campbell et al. (1993) we calculate stock i's abnormal trading volume $AbVolume_{it}$ as

$$AbVolume_{it} = \log(VOL_{it}) - \log(Median(VOL_{t-1}, VOL_{t-2}, ..., VOL_{t-n})) \quad (7)$$

where VOL is either the daily or the weekly trading volume, and $n = 252$ for daily volume or $n = 52$ for weekly volume.

Similarly, liquidity is found to significantly affect stock returns (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Datar et al., 1998). We proxy daily liquidity with the closing bid-ask spread, often called the quoted spread, calculated as the difference between the closing bid and ask prices divided by the price midpoint.:[10] Finally, we control for firm size using the market capitalization ($MCAP_{it}$)[11]

3 Results

We start by investigating how the *level* of company ESG, proxied by the Refinitiv ESG score, is linked to stock returns. We move on to ask how ESG news at the company level interacts with returns, before finally looking at economy-wide concerns about ESG or market uncertainty.

3.1 Relationship between ESG Scores and Stock Returns

We begin by evaluating the relationship between stock returns and the overall ESG score, as well as environmental, social and governance subscores. This establishes the general relationship between a company's sustainability level and its stock returns. The key findings are presented in Table 5, which shows that both the aggregate ESG, and the individual (E, S and G) scores are significant in explaining stock returns. The coefficients are negative, hence the companies with the highest ESG scores experience the lowest returns, implying that sustainable companies deliver inferior returns.[12] We view this result as a confirmation of the empirical

[10] A weekly spread is constructed as the average of the spreads over a given week.

[11] Market cap is estimated as the closing price times ds the number of shares outstanding. The weekly market capitalization is taken as the market capitalization of the last trading day of the week.

[12] In the appendix we show estimates of a panel data regression with similar negative and significant relationships. Throughout this section, we mainly use panel data regressions with company-fixed effects and robust standard errors. In order to test the validity of this model, we perform F-tests to check whether the intercepts differ. We find significance at the 5% level, indicating that the fixed effects are non-zero. Subsequently, we also test endogeneity using the Hausman-test with a 5% significance level. We find that endogeneity might be present, hence panel data

literature's findings of a negative relationship between cost of capital and ESG: High quality ESG firms have lower costs of capital (and hence lower expected returns).

3.2 ESG concerns at the company level

We next consider our measure of attention to a company, measured using abnormal Google Search Volume on the individual company ($AbISV_i$). Extraordinary attention to the company can be both due to negative or positive news. We argue that the increased attention will increase public awareness of the company, and thus reduse noise in the public view of the company's ESG profile. This is similar to the argument of Avramov et al. (2022) about variability of ESG ranking, and the effect of increases in precision of ESG ranking. With this arguement, a company with a high ESG ranking will benefit from social media exposure, as more people will discover the company and its high-quality ESG, and we expect the stock price reaction to be increasing in ESG quality.

The Google Search Volume at the company level is available at a weekly frequency. We therefore investigate to what degree weekly returns is affected by ESG issues. In Table 6 we show the results of regressions with weekly returns as dependent variable. Note that there is some uncertainty about what is the relevant *timing* of the effects. We don't know when during a week the social media attention spikes, it could be at the end of the week, after the market closes on friday. People's reactions to what they read may also take time. We therefore look at both returns the same week (contemporaneous) (Panel A), and the next week (lagged) (Panel B).

The models with only the search volume (Column (1) in both panels) show a negative and significant relationship between abnormal search volumes on individual companies and stock returns. That is, increased attention to companies is associated with low returns. These results are consistent with results from Chen (2017) and Bijl et al. (2016).

But our interest here is on the variables linked to ESG. For the contemporaneous estimation in Panel A, there is no significant effect, albeit most of the coefficients on the ESG variables are positive. The next-week results, however, have significantly positive coefficients on all ESG-related variables. Thus, when investors pay attention to individual company information, they seem to pay extra attention to their ESG level(s). Companies with higher ESG are less affected by the general negative effect of attention.

This observation lead us to conclude that high company attention is linked to an increase

regressions with fixed effects might be more appropriate than panel data regressions with random effects. In all regressions, we include abnormal volume, bid-ask spread and market capitalization as control variables.

in prices of high-quality ESG firms.

3.3 Economy-wide ESG concerns

We move on to consider social media interest in ESG issues, independent of company, and relate this to companies' ESG scores. We investigate how the ESG, environmental, social and governance scores affect daily stock returns when the public show interest in sustainability topics.

3.3.1 Google Searches on ESG Topics

The Google measure used in this investigation looks at the public interest in ESG topics independent of company. When the public is fired up about ESG issues, they will re-evaluate their view of companies' ESG status. The idea is the same as in the previous analysis, that increased attention will lower the public's uncertainty about a company's ESG status, the impetus is just not coming from news about the company itself.

These Google measures are available at a daily frequency. We therefore investigate how attention to sustainability topics affect daily stock returns. Because of the similar timing issue as before, we investigate both returns the same day and the next day. Table 7 shows the results. If we start with the same-day results in Panel A. Looking at the coefficients of increased attention on its own, (i.e. the coefficients on $AbSVI$ withouth interaction terms) it is negative. Days with increased attention to ESG topics in general are associated with lower returns. It is worth pointing out that we don't know whether these are good or bad news, just that there is increased attention. It is possible that the increased attention is predominately due to negative news, such as increased worry about the climate, oil spills, etc, that lead to the whole market falling. We will in some of our later analysis try to look at this, by estimating the sentiment of the news (the mood). We note that some of this general effect seem to be reversed the next day, from the results in panel B.

Of chief interest for us is however the interaction terms, where we ask to what degree the quality of a company's ESG modifies the relationship. Here again we observe, in the contemporaneous estimates, positive and significant coefficients on the ESG, E and G measures. The S measure is also positive, but not significant. The corresponding lagged coefficients in Panel B are not significant. We thus have the same conclusion as the previous estimation. Companies with high ESG scores benefit from the increased attention.

3.3.2 Twitter Volume on ESG topics

Let us now consider media traffic on Twitter about ESG topics as an alternative to the abnormal Google Search measure used in the previous subsection. The idea is the same, times with high focus on ESG in the economy are also times of increased awareness of the ESG scores of companies, leading to improved precision in public estimates of company ESG scores. We however improve on the previous analysis by also decomposing the twitter mentions. We study tweets containing "climate change," "corporate governance," "ESG," "social responsibility" and "sustainability," and use them as measures of engagement on ESG topics. These keywords are related to different factors of ESG, and are thus studied in relation to their appropriate score(s). We use "climate change" as a measure of engagement on the environmental factor and "social responsibility" as a measure of engagement on the social factor. Both "corporate governance" and "social responsibility" are used as measures of engagement on the governance factor, as the latter word may also contain tweets on "corporate social responsibility." Additionally, all five keywords are used as measures of engagement on overall ESG. As observed in the data section, there is low correlation between the volume of tweets containing the different words. We therefore study all five keywords separately.

We first evaluate the volume of tweets containing either of the five keywords explain stock returns, and then add interaction terms with ESG Scores. These interaction terms are of primary interest to our analysis.

Table 8 shows how the daily volume of tweets for each keyword are related to stock return and how this depends on companies' ESG scores. Overall, the results using Twitter are much weaker than the corresponding results using Google search volume. Model (1) for each keyword indicate that there is no conclusive relationship between the amount of tweets and stock returns. More tweets about "sustainability," "climate change" and "corporate governance" affect stock returns negatively, while more tweets about "social responsibility" is positively related to stock returns. We find that the impact on stock returns of Twitter volume on "climate change" and "social responsibility" depend on the environmental score, and the ESG and governance score, respectively. More engagement on Twitter related to "climate change" seems to affect the stock returns of companies with high environmental score negatively, observed in model (3) of "climate change." In addition, companies with high ESG and governance score are slightly negatively affected by increased buzz related to "social responsibility" on Twitter, seen in model (2) and (4) of "social responsibility." In general, we observe that there are few significant relationships. Engagement itself seems to affect stock returns of companies with different ESG scores similarly.

It is hard to summarize these results, they are pointing in different directions. Relative to the results using Google search they are much less consistent. It may be that Twitter is more noisy. To try to reduce the noise we therefore introduce some additional information about each Tweet, namely whether it is viewed as good or bad news. We therefore classify the tenor of the tweets, which we do using sentiment and mood estimation.

Twitter mood and ESG We study the content of each tweet by performing a sentiment analysis. This allows us to determine whether the content is positive, neutral or negative. When the sentiments are studied together, an overall mood may be established. We evaluate whether the daily mood can explain stock returns. Additionally, we study the amount of positive and negative tweets separately to gain insight into which sentiment impacts stock returns the most. For the keywords "social responsibility" and "sustainability," the mood on Twitter is positive for the studied period. For "corporate governance" and "ESG" more than 98% of the days have a positive mood.

The subtables of Table 9 show the relationships between the daily sentiment on Twitter of each keyword and the stock returns of companies, interacted with ESG, environmental, social and governance scores. Let us start by looking at a consistent result across these estimations, the results for *MOOD*. This variable is calculated as a difference between the number of positive and negative tweets. When it is high, the market is in a good mood. A negative coefficient on the MOOD variable thus has the interpretation that returns are higher when the market is in a negative mood. If we look across the estimations, the interaction terms between MOOD and the ESG variables are consistently negative, with most of them being significant. Thus, in times of negative views (large concerns) about ESG, high ESG firms have higher returns. This adds to our earlier findings. We earlier used measures of heightened ESG interest that did not distinguish between good and bad news. The MOOD result argues that of these two, it is the times of *negative* ESG concerns where high-quality firms do best (have higher returns).

There is however some variation. For example, the impact on stock returns for the Twitter mood related to "climate change," however, is not affected by ESG scores, shown by model (2) and (3) in the "climate change" table. A possible reason for this is that the usage of "climate change" on Twitter to a greater extent reflects public engagement rather than investor interest. The high volume of tweets containing the word "climate change" and the low correlation with the other keywords that deal with more finance-related topics, as presented in the data section, may support this presumption. Groß-Klußmann et al. (2019) find that the sentiment of experts tweeting about financial topics is more important than the public sentiment in explaining stock returns. Hence, the studied words' relation to finance and investments may be important for explaining stock returns of sustainable companies.

When investigating the mood it is not clear whether the amount of positive or negative tweets has the most influence on stock returns. Our results in the subtables of Table 9 indicate that the impact of the amount of negative tweets on stock returns is more often dependent on ESG scores compared to the amount of positive tweets. Nevertheless, no general conclusion can be drawn about the direction of this dependency. On one hand, a high amount of negative tweets related to "ESG" contributes positively to the returns of companies with high ESG score, presented in model (6) of the "ESG" subtable. On the other hand, a low amount of negative tweets related to "social responsibility" is associated with lower stock returns for high-ranked companies, as seen in model (10), (11) and (12) in the "social responsibility" subtable.

To complement our analysis of same-day mood, in Table 10 we also show analysis of next-day returns. Here, most of the interactions between MOOD and ESG switch signs relative to the previous estimation. This would indicate that some of the same-day effects are reversed the next day.

Specifically, we observe that the mood on Twitter for all keywords are significant in predicting stock returns. This is observed in model (1) for all keywords. However, the mood might predict both positive and negative returns, depending on the keyword studied. A positive mood related to "ESG" and "sustainability" is linked to higher stock returns, while a negative mood related to "climate change," "social responsibility" and "corporate governance" is linked to higher returns. When we investigate the impact of the mood on stock returns of companies with high and low scores, we find that a positive mood for all keywords is linked to higher returns the following day for high-ranked companies. This relationship is opposite of what we found for the mood and stock returns of sustainable companies the same day. This may occur as the behavior of investors are different for positive and negative sentiments. A positive sentiment increases the adoption of future goals, while a negative sentiment triggers a focus on immediate concerns (Liberman and Trope, 1998; Eyal et al., 2004; Bar-Anan et al., 2006; Fujita et al., 2006; Labroo and Patrick, 2009). Thus, an investor might be likely to invest in sustainable companies immediately when there is more public concern about sustainability. However, in the long run, the positive sentiment may influence investor to invest in sustainable companies due to a belief in long-term profitability. Accordingly, sustainable companies may generate higher daily returns when there is more negativity on Twitter related to sustainability, but on a longer term generate higher returns when there is more positivity.

To summarize our results so far, we have shown that companies with higher ESG scores generate higher returns on days with heightened ESG concerns, particularly when the mood on Twitter is negative.

3.3.3 General uncertainty in the economy – VIX

Our final set of estimates moves away from social media to times of uncertainty in the economy. The analysis is motivated by the literature's finding that high quality ESG companies seem more resilient during two recent crises, the 2008 financial crisis and the Covid Pandemic in 2020. In both cases the prices of highly ranked ESG shares fell relatively less. Neither of these crises were particularly related to ESG issues, they were periods of increases in market-wide volatility. To test whether periods of high volatility may have similar effects as periods of increased attention to ESG, we replace our measures of abnormal interest in ESG with periods of heightened levels of the VIX.

Table 11 shows regressions explaining (daily) stock return with $AbVIX$, the measure of heightened level of uncertainty (the deviation of VIX from its one year rolling median), interacted with company measures of ESG scores.

We note that stock returns and deviations in VIX from its one year rolling median have a negative and significant relationship. This is a well-known observation; stock prices fall when market uncertainty is high (Whaley, 2000; Giot, 2005; Banerjee et al., 2007). However, our interest is centered on the interaction terms with ESG, environmental, social and governance scores. Here we find that all of these are significantly positive. Companies with high ESG scores are associated with higher returns when market uncertainty is abnormally high. This is not reversed the next day, for the interaction with the E score we see a significantly positive coefficient also for the next-day return results, while the other coefficients are insignificant.[13]

Our results indicate that the resiliency of high ESG ranked firms goes beyond the two mentioned crises, and is a general feature of episodes of extra volatility. Periods of high volatility are similar to periods of heightened ESG interest, short-term returns increase for firms with a high ESG ranking.

3.4 Robustness

In the reported estimations we have not included standard risk measures, such as Fama-French factors. To check the validity of our results, we have also tested the presented relationships using abnormal returns, estimated as residuals of a Fama-French three-factor model, as dependent

[13]We have performed similar estimations for another measure of innovations to the VIX index – daily changes in VIX level. These results are similar, and therefore only provided in the appendix.

variable. This produces similar results, and the conclusions drawn from using return as dependent variable remain unchanged. We conclude that our results are not due to our leaving out these factors.

4 Conclusion

Our concern in this paper is the whether there is a link between ESG properties of firms and short-term changes in stock prices. The theoretical motivation for the analysis is twofold. First, the analysis of Cornell (2021), who argues that increases in concern about ESG, which he interprets as changes to utility, will lead to short-term demand for high-quality ESG stocks, pushing up prices in the short-term, but leading to lower (long term) expected returns. Second, the intuition of Avramov et al. (2022) that changes to the *precision* of ESG rankings will lead to similar changes in stock demand. These arguments lead us to investigate whether periods of heightened concern about ESG, either at the firm or economy level, are also periods with changes in relative prices between "good" or "bad" (in the ESG sense) companies.

In our analysis we use ESG scores provided by Refinitiv to assess the sustainability level of a company. Investor concerns related to these companies, the general stock market and ESG topics are measured using Google search volumes, Twitter and VIX. Our dataset consists of 2030 companies trading on NYSE or NASDAQ for the period 2010-2019.

We first analyze the ESG level effect, and establish that the stocks of companies with high ESG scores on average underperform. This is a confirmation of a large theoretical and empirical literature arguing that expected returns are decreasing in ESG quality.

Our second set of analyses looks at ESG concerns at the company level. We investigate how public attention to ESG topics and companies, measured by Google search volumes, is linked to stock returns. We find that high search volumes on ESG topics are related to higher stock returns for companies with high ESG, environmental and governance scores.

Our third set of analyses investigates ESG concerns at the economy level. We use data from social media to investigate this. For example, we use 42 million tweets that contain either of the words "climate change," "corporate governance," "ESG," "social responsibility" and "sustainability" to evaluate whether stock returns are affected by public engagement on ESG topics, and how this may depend on companies' ESG scores. In general, we find that the impact of the amount of tweets related to ESG topics on stock returns shows little dependence on ESG scores. Next, we perform sentiment analysis on each tweet and construct variables capturing the overall Twitter mood related to these topics. The impact of the mood related to ESG topics on stock returns is highly affected by the ESG scores. A more negative ESG mood on Twitter is associated with higher stock returns for companies with high ESG scores.

Our final set of analyses links estimates of the level uncertainty in the economy (the VIX index) and ESG concern, motivated by empirical observations of resiliency in the crises of 2008 and 2020. We find that the resiliency of high ESG ranked firms goes beyond the two mentioned crises, and is a general feature of episodes of high economy-wide volatility.

As a general conclusion, our analysis have shown the presence of short-term stock price reactions linked to broad ESG issues, not limited to single company reactions to specific news about that company. Admittedly, our methods only allow for a relatively broad-brush approach, other methods are necessary to get into more specific causality and stock price magnitude discussions.

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Table 1: Descriptive statistics for the Refinitiv ESG scores

The table describes ESG, (E)nvironmental, (S)ocial and (G)overnance scores obtained from Refinitiv for the sample of US companies, in the period 2010-2019. Data for 2030 companies. Panel A: Descriptive statistics: Mean, median, minimum and maximum scores. Panel B: Correlation between the four different scores (ESG, E, S and G).

Panel A: Descriptive statistics

	Measure			
Score	Mean	Median	Min	Max
ESG score	40.79	37.30	0.26	95.14
(E)nvironmental score	25.03	13.05	0.00	98.53
(S)ocial score	42.30	38.36	0.60	97.88
(G)overnance score	50.05	50.62	0.04	98.72

Panel B: Correlations

	ESG score	(E)nvironmental score	(S)ocial score
(E)nvironmental score	0.859		
(S)ocial score	0.875	0.730	
(G)overnance score	0.705	0.451	0.373

Table 2: Characterizing the abnormal Tweet volume by keyword

The Twitter volume is based on tweets containing the keywords "climate change," "corporate governance," "ESG," "social responsibility" or "sustainability." Abnormal volume is calculated as $AbTV_t = \log(TV_t) - \log(Median(TV_{t-7}, TV_{t-14}, ..., TV_{t-364}))$, where TV is based on the different keywords. In the table we show the correlations between $AbTV$ calculated using each of the five keywords.

Keyword:	Climate change	Corporate governance	ESG	Social responsibility
Corporate governance	0.284			
ESG	0.304	0.509		
Social responsibility	0.245	0.383	0.423	
Sustainability	0.389	0.579	0.684	0.445

Table 3: Example tweets with polarities

The table illustrates the generation of sentiment. On the left is the Tweet, the sentiment indicated by each of the three methods (TextBlob, VADER and Flair), and the final total polarity.

Tweet	TextBlob	VADER	Flair	Total Polarity
Social responsibility is not just about selling the product but enhancing the quality of life for all.	0	0.033	Positive	Positive
@realDonaldTrump Of course, her happiness, the world's happiness, and a bright and wonderful future can only be accomplished when your future as US president ends and nations unite in a common purpose to slow down or stop warming world temperatures and related adverse climate change.	0.2120	0.9274	Positive	Positive
Corporate governance: What kind of world would you like your children and your children's' children to inherit? http://ow.ly/39Ijn	0.3	0.3612	Negative	Positive
More Funds Are Formally Considering ESG in Their Investment Processes https://t.co/QqFS0oTIvR #esg	0.5	0	Negative	Neutral
Pope Francis tells oil chiefs to keep it in the ground https://t.co/btdTdhBHZl vía @ClimateHome #ESG	0	0	Negative	Neutral
Rise in index funds creates corporate governance risks #shareholderactivism https://t.co/51AhmxdTXQ	0	0	Negative	Neutral
You want to reduce the anxiety about #climatechange @ScottMorrisonMP - then fucking do something about it. #triggeredbygreta #auspol #climateemergency @GretaThunberg #ClimateCrisis #UnitedNations https://t.co/ZN5oluJ5O4	-0.6	-0.1027	Negative	Negative
Carrying a plastic bag in Kenya is now punishable with jail time https://t.co/rZRIuuOozK via @qzafrica #environment #sustainability	-0.1	-0.4404	Negative	Negative
Keep the environment and sustainability, because after all destroyed we will realize the money ill be eaten. #fz7	-0.5	-0.7184	Positive	Negative

Table 4: The degree to which tweet classifications differ across methods

The tables illustrate the degree to which sentiment agrees across methods. We consider three methods (TextBlob, VADER and Flair). For each combination of two, we count the number of tweets with the different classifications.

Panel A

VADER \ Flair	Positive	Negative	Total
Positive	11 441 367	4 703 288	16 144 655
Neutral	9,532,326	4,737,648	14,269,974
Negative	3,629,199	8,043,757	11,672,956
Total	24,602,892	17,484,693	42,087,585

Panel B

TextBlob \ Flair	Positive	Negative	Total
Positive	10,506,046	5,832,057	16,338,103
Neutral	11,591,499	7,357,399	18,948,898
Negative	2,505,347	4,295,237	6,800,584
Total	24,602,892	17,484,693	42,087,585

Panel C

TextBlob \ VADER	Positive	Neutral	Negative	Total
Positive	9,622,642	3,437,769	3,277,692	16,338,103
Neutral	4,954,116	9,368,874	4,625,908	18,948,898
Negative	1,567,897	1,463,331	3,769,356	6,800,584
Total	16,144,655	14,269,974	11,672,956	42,087,585

Table 5: Explaining stock returns with ESG

Explaining stock returns with ESG, environmental (E), social (S) and governance (G) scores, controlling for daily trading volume *AbVolume*, liquidity *BidAsk* and market capitalization *MCAP*. Daily returns R_{it} in percent. ESG scores normalized to lie in the interval $[0, 1]$. *AbVolume* is the difference between todays volume and "normal" volume, as specified in eqn (7). *BidAsk* is the difference between closing bid and ask prices, divided by the quote midpoint. *MktCap* is the logarithm of market capitalization. Standard errors are calculated clustering on dates. Results for an OLS regression. An appendix provides results for a regression including fixed company effects. Significance levels are indicated as $*p < 0.05$, $**p < 0.01$.

	Dependent variable: Daily Return			
	(1)	(2)	(3)	(4)
ESG_{it}	-0.147^{**}			
	(0.029)			
E_{it}		-0.072^{**}		
		(0.012)		
S_{it}			-0.076^{**}	
			(0.024)	
G_{it}				-0.084^{**}
				(0.018)
$AbVolume_{it}$	0.113^{**}	0.052^{*}	0.113^{**}	0.114^{**}
	(0.019)	(0.021)	(0.019)	(0.019)
$BidAsk_{it}$	−1.323	-3.843^{*}	−1.283	−1.375
	(1.515)	(1.813)	(1.515)	(1.519)
$MktCap_{it}$	0.015^{*}	0.002	0.009	0.007
	(0.007)	(0.007)	(0.008)	(0.007)
Constant	−0.072	0.140	−0.023	0.020
	(0.126)	(0.132)	(0.129)	(0.120)
Observations	2,664,947	1,807,045	2,664,947	2,664,947
Adjusted R^2	0.001	0.001	0.001	0.001

Table 6: Explaining Stock Returns with Company-level abnormal Google Search Volume and ESG

Explaining weekly stock returns of companies using Search Volume Index, *AbSVI*, on company names, interacted with ESG, environmental (E), social (S) and governance (G) scores, controlling for trading volume *AbVolume*, liquidity *BidAsk* and market capitalization *MCAP*. Returns (R) in percent. $AbSVI_i$ measures the abnormal Google search volume linked to Company i. ESG scores normalized to lie in the interval $[0, 1]$. *AbVolume* is the difference between todays volume and "normal" volume, as specified in eqn (7). *BidAsk* is the difference between closing bid and ask prices, divided by the quote midpoint. *MktCap* is the logarithm of market capitalization. Panel data regressions with company fixed effects. Robust standard errors. Significance level indicated as $*p < 0.05$, $**p < 0.01$.

Panel A: Returns the same week

	Dependent variable: Weekly return, R_{it}				
	(1)	(2)	(3)	(4)	(5)
$AbSVI_{it}$	-0.062^{*}	-0.123	-0.076^{*}	-0.037	-0.216
	(0.026)	(0.063)	(0.035)	(0.028)	(0.116)
$AbSVI_{it} \times \text{ESG}_{it}$		0.170			
		(0.111)			
$AbSVI_{it} \times \text{E}_{it}$			0.077		
			(0.063)		
$AbSVI_{it} \times \text{S}_{it}$				-0.066	
				(0.080)	
$AbSVI_{it} \times \text{G}_{it}$					0.330
					(0.197)
$AbVolume_{it}$	-0.613^{*}	-0.613^{*}	-0.613^{*}	-0.613^{*}	-0.614^{*}
	(0.251)	(0.251)	(0.251)	(0.251)	(0.252)
$BidAsk_{it}$	48.952^{**}	48.952^{**}	48.950^{**}	48.951^{**}	48.949^{**}
	(13.612)	(13.612)	(13.612)	(13.612)	(13.612)
$MCAP_{it}$	0.772^{**}	0.772^{**}	0.772^{**}	0.772^{**}	0.773^{**}
	(0.219)	(0.219)	(0.219)	(0.219)	(0.218)
R^2	0.002	0.002	0.002	0.002	0.002
No obs	581,655	581,655	581,655	581,655	581,655

Panel B: Returns the next week

	Dependent variable: Weekly return, R_{it}				
	(1)	(2)	(3)	(4)	(5)
$AbSVI_{i,t-1}$	-0.073^{**}	-0.182^{**}	-0.105^{**}	-0.140^{**}	-0.160^{**}
	(0.015)	(0.051)	(0.023)	(0.043)	(0.053)
$AbSVI_{i,t-1} \times ESG_{i,t-1}$		0.304^{**}			
		(0.110)			
$AbSVI_{i,t-1} \times E_{i,t-1}$			0.172^{**}		
			(0.054)		
$AbSVI_{i,t-1} \times S_{i,t-1}$				0.179^{*}	
				(0.083)	
$AbSVI_{i,t-1} \times G_{it-1}$					0.185^{*}
					(0.092)
$AbVolume_{i,t-1}$	-0.419^{*}	-0.420^{*}	-0.420^{*}	-0.419^{*}	-0.420^{*}
	(0.172)	(0.173)	(0.172)	(0.172)	(0.173)
$BidAsk_{i,t-1}$	40.266^{*}	40.267^{*}	40.263^{*}	40.269^{*}	40.264^{*}
	(17.086)	(17.086)	(17.085)	(17.087)	(17.086)
$MCAP_{i,t-1}$	-1.067^{**}	-1.067^{**}	-1.067^{**}	-1.067^{**}	-1.066^{**}
	(0.119)	(0.119)	(0.119)	(0.119)	(0.118)
R^2	0.003	0.003	0.003	0.003	0.003
No obs	581,600	581,600	581,600	581,600	581,600

Table 7: Explaining stock returns with google search interest in ESG topics

Explaining stock returns using search volume indices, SVIs, on ESG, social, environmental and governance topics, interacted with company ESG, environmental (E), social (S) and governance (G) scores, controlling for trading volume *AbVolume*, liquidity *BidAsk* and market capitalization *MCAP*. Returns R_{it} in percent. *AbSVI* measures the (economy-wide) abnormal Google search volume linked to the indicated ESG topic(s), i.e. $AbsVI_G$ is the abnormal search volume for Governance specific keywords. ESG scores normalized to lie in the interval $[0, 1]$. *AbVolume* is the difference between todays volume and "normal" volume, as specified in eqn (7). *BidAsk* is the difference between closing bid and ask prices, divided by the quote midpoint. *MktCap* is the logarithm of market capitalization. Panel data regressions with company fixed effects. Robust standard errors. Significance level indicated as $*p < 0.05$, $**p < 0.01$.

Panel A: Same Day returns

	Dependent variable: Daily return,R_{it}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AbSVI_{ESG,t}$	-0.017^{**}	-0.070^{**}						
	(0.005)	(0.013)						
$AbSVI_{ESG,t} \times \text{ESG}_t$		0.130^{**}						
		(0.024)						
$AbSVI_{E,t}$			-0.016^{**}	-0.026^{**}				
			(0.003)	(0.005)				
$AbSVI_{E,t} \times \text{E}_t$				0.043^{**}				
				(0.010)				
$AbSVI_{S,t}$					-0.016^{**}	-0.027^{**}		
					(0.005)	(0.010)		
$AbSVI_{S,t} \times \text{S}_t$						0.027		
						(0.019)		
$AbSVI_{G,t}$							0.045^{**}	-0.023
							(0.005)	(0.015)
$AbSVI_{G,t} \times \text{G}_t$								0.136^{**}
								(0.025)
$AbVolume_{it}$	0.115^{**}	0.115^{**}	0.115^{**}	0.115^{**}	0.115^{**}	0.115^{**}	0.112^{**}	0.112^{**}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.705^{*}	-1.697^{*}	-1.702^{*}	-1.696^{*}	-1.703^{*}	-1.702^{*}	-1.699^{*}	-1.696^{*}
	(0.684)	(0.685)	(0.685)	(0.685)	(0.685)	(0.685)	(0.684)	(0.684)
$MCAP_{it}$	0.148^{**}	0.148^{**}	0.148^{**}	0.148^{**}	0.147^{**}	0.147^{**}	0.148^{**}	0.148^{**}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Panel B: Next Day returns

	Dependent variable: Daily return, R_{it}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AbSVI_{ESG,\ t-1}$	0.030^{**}	0.033^{*}						
	(0.005)	(0.013)						
$AbSVI_{ESG,\ t-1} \times \text{ESG}_{i,t-1}$		-0.007						
		(0.025)						
$AbSVI_{E,\ t-1}$			0.031^{**}	0.029^{**}				
			(0.003)	(0.005)				
$AbSVI_{E,\ t-1} \times \text{E}_{i,t-1}$				0.010				
				(0.011)				
$AbSVI_{S,\ t-1}$					0.043^{**}	0.045^{**}		
					(0.004)	(0.010)		
$AbSVI_{S,\ t-1} \times \text{S}_{i,t-1}$						-0.0045		
						(0.020)		
$AbSVI_{G,\ t-1}$							0.082^{**}	0.095^{**}
							(0.005)	(0.016)
$AbSVI_{G,\ t-1} \times \text{G}_{i,t-1}$								-0.026
								(0.026)
$AbVolume_{i,t-1}$	0.032^{**}	0.032^{**}	0.032^{**}	0.032^{**}	0.031^{**}	0.031^{**}	0.030^{**}	0.030^{**}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$BidAsk_{i,t-1}$	0.344	0.344	0.337	0.338	0.339	0.339	0.351	0.351
	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)
$MCAP_{i,t-1}$	-0.1908^{**}	-0.191^{**}	-0.191^{**}	-0.191^{**}	-0.190^{**}	-0.191^{**}	-0.191^{**}	-0.191^{**}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305

Table 8: Explaining stock returns using abnormal Twitter volume, interacted with ESG

Explaining stock returns with abnormal Twitter volume, *AbTV*, for the five keywords, interacted with companies *ESG*, environmental *(E)*, social *(S)* and governance*(G)* scores, controlling for trading volume *AbVolume*, liquidity *BidAsk* and market capitalization *MCAP*. Returns R_{it} in percent. The twitter Abnormal volume $AbTV$ measures the difference between the current number of tweets relative to a moving average over the previous year, as specified in equation (3). Note that $AbTV$ is calculated separately for the various keywords. ESG scores normalized to lie in the interval $[0, 1]$. *AbVolume* is the difference between todays volume and "normal" volume, as specified in eqn (7). *BidAsk* is the difference between closing bid and ask prices, divided by the quote midpoint. *MktCap* is the logarithm of market capitalization. Panel data regressions with company fixed effects. Robust standard errors. Significance level indicated as $*p < 0.05, **p < 0.01$.

	Dependent variable: Daily return, R_{it}														
	Keyword:														
	ESG		Sustainability		Climate change			Social responsibility				Corporate governance			
	(1)	(2)	(1)	(2)	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(1)	(2)	(3)
$AbTV_t$	−0.006	−0.0248*	−0.030**	−0.041**	−0.027**	−0.015	−0.021**	0.035**	0.052**	0.023**	0.083**	−0.036**	−0.032**	−0.049**
	(0.005)	(0.012)	(0.005)	(0.014)	(0.004)	(0.009)	(0.005)	(0.004)	(0.009)	(0.008)	(0.011)	(0.004)	(0.011)	(0.011)
$AbTV_t \times ESG_{it}$		0.045		0.027**		−0.031			−0.042*				0.010	
		(0.024)		(0.027)		(0.018)			(0.019)				(0.021)	
$AbTV_t \times E_{it}$							−0.024*							
							(0.012)							
$AbTV_t \times S_{it}$										0.029				
										(0.016)				
$AbTV_t \times G_{it}$											−0.095**			0.024
											(0.018)			(0.019)
$Volume_{it}$	0.114**	0.114**	0.115**	0.115**	0.115**	0.115**	0.115**	0.113**	0.113**	0.113**	0.113**	0.115**	0.115**	0.115**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	−1.705*	−1.706*	−1.706*	−1.707*	−1.710*	−1.709*	−1.710*	−1.691*	−1.655*	−1.692*	−1.691*	−1.712*	−1.711*	−1.711*
	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.147**	0.147**	0.146**	0.147**	0.149**	0.149**	0.149**	0.149**	0.149**	0.149**	0.149**	0.146**	0.146**	0.146**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Table 9: Explaining stock returns with Twitter sentiment and mood, interacted with company ESG

Explaining stock returns with abnormal positive Twitter volume, $AbTV^+$, abnormal negative Twitter volume, $AbTV^-$, and the MOOD. The MOOD is the overall Twitter sentiment. Including estimations interacted with company ESG, environmental (E), social (S) and governance (G) scores. Controlling for daily trading volume *AbVolume*, liquidity *BidAsk* and market capitalization *MCAP*. Returns R_{it} in percent. The twitter Abnormal volume $AbTV$ measures the difference between the current number of tweets relative to a moving average over the previous year, as specified in equation (3). Calculated separately for positive, neutral, and negative sentiment. Note that $AbTV$ is calculated separately for the various keywords. In the next tables each table relate to a separate keyword. MOOD is the overall sentiment of tweets. ESG scores normalized to lie in the interval [0, 1]. *AbVolume* is the difference between todays volume and "normal" volume, as specified in eqn (7). *BidAsk* is the difference between closing bid and ask prices, divided by the quote midpoint. *MktCap* is the logarithm of market capitalization. Panel data regressions with company fixed effects. Robust standard errors. Significance level indicated as $*p < 0.05,^{**} p < 0.01$.

Panel A: Keyword: ESG

	Dependent variable: Daily return, R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
$MOOD_t$	-0.388^{**}	-0.199^{**}				
	(0.019)	(0.033)				
$MOOD_t \times ESG_{it}$		-0.386^{**}				
		(0.053)				
$AbTV_t^+$			-0.033^{**}	-0.046^{**}		
			(0.004)	(0.011)		
$AbTV_t^+ \times ESG_{it}$				0.031		
				(0.021)		
$AbTV_t^-$					-0.040^{**}	-0.050^{**}
					(0.004)	(0.004)
$AbTV_t^- \times ESG_{it}$						0.064^{**}
						(0.007)
$AbVolume_{it}$	0.115^{**}	0.115^{**}	0.116^{**}	0.116^{**}	0.115^{**}	0.114^{**}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.62^{*}	-1.61^{*}	-1.71^{*}	-1.71^{*}	-1.70^{*}	-1.69^{*}
	(0.686)	(0.686)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.167^{**}	0.172^{**}	0.146^{**}	0.146^{**}	0.146^{**}	0.147^{**}
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Table 9: (Continued)

Panel B: Keyword: Sustainability

	Dependent variable: Daily return, R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
$MOOD_t$	-0.620^{**}	-0.495^{**}				
	(0.028)	(0.037)				
$MOOD_t \times ESG_{it}$		-0.202^{**}				
		(0.039)				
$AbTV_t^+$			-0.022^{**}	-0.031^{*}		
			(0.005)	(0.013)		
$AbTV_t^+ \times ESG_{it}$				0.020		
				(0.025)		
$AbTV_t^-$					-0.071^{**}	-0.070^{**}
					(0.005)	(0.013)
$AbTV_t^- \times ESG_{it}$						-0.002
						(0.024)
$AbVolume_{it}$	0.112^{**}	0.112^{**}	0.115^{**}	0.115^{**}	0.116^{**}	0.116^{**}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.554^{*}	-1.547^{*}	-1.705^{*}	-1.706^{*}	-1.697^{*}	-1.697^{*}
	(0.687)	(0.687)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.182^{**}	0.185^{**}	0.147^{**}	0.147^{**}	0.147^{**}	0.147^{**}
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.002	0.002	0.001	0.001	0.001	0.001
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Table 9: (Continued)

Panel C: Keyword: Climate change

	Dependent variable: Return								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MOOD_t$	−0.457**	−0.423**	−0.457**						
	(0.021)	(0.051)	(0.030)						
$MOOD_t \times ESG_{it}$		−0.083							
		(0.099)							
$MOOD_t \times E_{it}$			−0.002						
			(0.064)						
$AbTV_t^+$				−0.047**	−0.041**	−0.044**			
				(0.004)	(0.010)	(0.006)			
$AbTV_t^+ \times ESG_{it}$					−0.015				
					(0.019)				
$AbTV_t^+ \times E_{it}$						−0.015			
						(0.012)			
$AbTV_t^-$							−0.0119**	−0.014**	−0.014**
							(0.003)	(0.003)	(0.003)
$AbTV_t^- \times ESG_{it}$								0.047**	
								(0.006)	
$AbTV_t^- \times E_{it}$									0.047**
									(0.006)
$AbVolume_{it}$	0.116**	0.116**	0.116**	0.116**	0.116**	0.116**	0.114**	0.114**	0.114**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	−1.654*	−1.654*	−1.654**	−1.708*	−1.708*	−1.709**	−1.703**	−1.695**	−1.665**
	(0.685)	(0.685)	(0.685)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.149**	0.149**	0.149**	0.15**	0.15**	0.15**	0.148**	0.149**	0.149**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Table 9: (Continued)

Panel D: Keyword: Social responsibility

	Dependent variable: Daily return, R_{it}											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$MOOD_t$	-0.068^{**}	0.103^{**}	0.061^{**}	0.008								
	(0.016)	(0.020)	(0.019)	(0.019)								
$MOOD_t \times ESG_{it}$		-0.428^{**}										
		(0.030)										
$MOOD_t \times S_{it}$			-0.313^{**}									
			(0.026)									
$MOOD_t \times G_{it}$				-0.155^{**}								
				(0.018)								
$AbTV_t^+$					0.037^{**}	0.052^{**}	0.025^{**}	0.08^{**}				
					(0.004)	(0.009)	(0.008)	(0.010)				
$AbTV_t^+ \times ESG_{it}$						-0.036^{*}						
						(0.018)						
$AbTV_t^+ \times S_{it}$							0.028					
							(0.015)					
$AbTV_t^+ \times G_{it}$								-0.086^{**}				
								(0.017)				
$AbTV_t^-$									0.041^{**}	0.066^{**}	0.06^{**}	0.061^{**}
									(0.003)	(0.008)	(0.008)	(0.009)
$AbTV_t^- \times ESG_{it}$										-0.062^{**}		
										(0.017)		
$AbTV_t^- \times S_{it}$											-0.046^{**}	
											(0.015)	
$AbTV_t^- \times G_{it}$												-0.041^{**}
												(0.016)
$AbVolume_{it}$	0.114^{**}	0.114^{**}	0.114^{**}	0.114^{**}	0.113^{**}	0.113^{**}	0.113^{**}	0.113^{**}	0.113^{**}	0.113^{**}	0.113^{**}	0.113^{**}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.711^{*}	-1.674^{*}	-1.682^{*}	-1.703^{*}	-1.688^{*}	-1.687^{*}	-1.688^{*}	-1.687^{*}	-1.702^{*}	-1.701^{*}	-1.701^{*}	-1.701^{**}
	(0.685)	(0.685)	(0.685)	(0.685)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.147^{**}	0.161^{**}	0.158^{**}	0.151^{**}	0.149^{**}	0.149^{**}	0.149^{**}	0.149^{**}	0.148^{**}	0.148^{**}	0.148^{**}	0.148^{**}
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Table 9: (Continued)

Panel E: Keyword: Corporate governance

	Dependent variable: Daily return, R_{it}								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MOOD_t$	-0.038^{**}	0.078^{**}	0.035						
	(0.011)	(0.024)	(0.022)						
$MOOD_t \times ESG_{it}$		-0.28^{**}							
		(0.047)							
$MOOD_t \times G_{it}$			-0.145^{**}						
			(0.034)						
$AbTV_t^+$				-0.042^{**}	-0.055^{**}	-0.062^{**}			
				(0.004)	(0.009)	(0.010)			
$AbTV_t^+ \times ESG_{it}$					0.032				
					(0.018)				
$AbTV_t^+ \times G_{it}$						0.041^{*}			
						(0.017)			
$AbTV_t^-$							-0.028^{**}	-0.006	-0.025^{**}
							(0.003)	(0.006)	(0.007)
$AbTV_t^- \times ESG_{it}$								-0.054^{**}	
								(0.013)	
$AbTV_t^- \times G_{it}$									-0.006
									(0.012)
$AbVolume_{it}$	0.114^{**}	0.114^{**}	0.114^{**}	0.115^{**}	0.115^{**}	0.115^{**}	0.115^{**}	0.115^{**}	0.115^{**}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.699^{*}	-1.687^{*}	-1.696^{*}	-1.704^{*}	-1.704^{*}	-1.704^{*}	-1.710^{*}	-1.709^{*}	-1.710^{*}
	(0.685)	(0.685)	(0.685)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.148^{**}	0.152^{**}	0.149^{**}	0.146^{**}	0.146^{**}	0.146^{*}	0.147^{**}	0.147^{**}	0.147^{**}
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Table 10: Explaining (next day) stock returns with Twitter mood, interacted with ESG

Explaining (next week) stock return with Twitter mood, interacted with ESG, environmental (E), social (S) and governance (G) scores, controlling for daily trading volume *AbVolume*, liquidity *BidAsk* and market capitalization *MCAP*. Returns R_{it} in percent. MOOD it the normalized difference between the number of positive and negative tweets. ESG scores normalized to lie in the interval $[0, 1]$. *AbVolume* is the difference between todays volume and "normal" volume, as specified in eqn (7). *BidAsk* is the difference between closing bid and ask prices, divided by the quote midpoint. *MktCap* is the logarithm of market capitalization. Panel data regressions with company fixed effects. Robust standard errors. Significance level indicated as $*p < 0.05, **p < 0.01$.

	Dependent variable: Daily return, R_{it}													
Keyword:	ESG		Sustainability		Climate change			Social responsibility				Corporate governance		
	(1)	(2)	(1)	(2)	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(1)	(2)	(3)
$MOOD_{t-1}$	0.074**	−0.202**	0.250**	−0.008	−0.422**	−0.715**	−0.517**	−0.177**	−0.320**	−0.325**	−0.219**	−0.025*	−0.232**	−0.107**
	(0.018)	(0.033)	(0.025)	(0.036)	(0.021)	(0.049)	(0.028)	(0.016)	(0.020)	(0.020)	(0.019)	(0.012)	(0.023)	(0.021)
$MOOD_{t-1} \times ESG_{i,t-1}$		0.565**		0.415**		0.716**			0.360**				0.496**	
		(0.055)		(0.041)		(0.107)			(0.031)				(0.047)	
$MOOD_{t-1} \times E_{i,t-1}$							0.371**							
							(0.073)							
$MOOD_{t-1} \times S_{i,t-1}$										0.361**				
										(0.027)				
$MOOD_{t-1} \times G_{i,t-1}$											0.085**			0.161**
											(0.019)			(0.035)
$AbVolume_{i,t-1}$	0.034**	0.034**	0.035**	0.035**	0.034**	0.034**	0.034**	0.034**	0.035**	0.034**	0.034**	0.033**	0.034**	0.033**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$BidAsk_{i,t-1}$	0.328**	0.307**	0.283**	0.271**	0.393**	0.389**	0.391**	0.331**	0.301**	0.299	0.326**	0.252**	0.333**	0.333**
	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)
$MCAP_{i,t-1}$	−0.195**	−0.202**	−0.205**	−0.211**	−0.190**	−0.192**	−0.191**	−0.192**	−0.203**	−0.205**	−0.194**	−0.191**	−0.197**	−0.192**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No obs	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305

Table 11: Explaining stock returns with ESG and VIX

Explaining stock returns with changes in VIX, interacting with ESG, environmental (E), social (S) and governance (G) score, controlling for daily trading volume *AbVolume*, liquidity *BidAsk* and market capitalization *MCAP*. *AbVIX* is the deviation in VIX from its one year rolling median, Returns R_{it} in percent. ESG scores normalized to lie in the interval $[0, 1]$. *AbVolume* is the difference between todays volume and "normal" volume, as specified in eqn (7). *BidAsk* is the difference between closing bid and ask prices, divided by the quote midpoint. *MktCap* is the logarithm of market capitalization. Panel data regressions with company fixed effects. Robust standard errors. Significance level indicated as $*p < 0.05$, $**p < 0.01$.

Panel A: Explaining Same Day Return

	Dependent variable: Daily return, R_{it}				
	(1)	(2)	(3)	(4)	(5)
$AbVIX_t$	-0.8926^{**}	-0.964^{**}	-0.922^{**}	-0.905^{**}	-0.991^{**}
	(0.006)	(0.014)	(0.008)	(0.013)	(0.015)
$AbVIX_t \times ESG_{it}$		0.174^{**}			
		(0.031)			
$AbVIX_t \times E_{it}$			0.116^{**}		
			(0.021)		
$AbVIX_t \times S_{it}$				0.028^{**}	
				(0.028)	
$AbVIX_t \times G_{it}$					0.196^{**}
					(0.068)
$AbVolume_{it}$	0.137^{**}	0.137^{**}	0.137^{**}	0.137^{**}	0.137^{**}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$BidAsk_{it}$	0.881^{**}	0.889^{**}	0.888^{**}	0.882^{**}	0.892^{**}
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
$MCAP_{it}$	0.18^{**}	0.18^{**}	0.18^{**}	0.18^{**}	0.18^{**}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.010	0.010	0.010	0.010	0.010
No obs	2,662,419	2,662,419	2,662,419	2,662,419	2,662,419

Panel B: Explaining Next Day Return

	Dependent variable: Daily return, R_{it}				
	(1)	(2)	(3)	(4)	(5)
$AbVIX_{t-1}$	0.141^{**}	0.125^{**}	0.124^{**}	0.129^{**}	0.136^{**}
	(0.006)	(0.052)	(0.008)	(0.014)	(0.015)
$AbVIX_{t-1} \times ESG_{i,t-1}$		0.0403			
		(0.032)			
$AbVIX_{t-1} \times E_{i,t-1}$			0.066^{**}		
			(0.075)		
$AbVIX_{t-1} \times S_{i,t-1}$				0.028	
				(0.092)	
$AbVIX_{t-1} \times G_{i,t-1}$					0.01
					(0.028)
$AbVolume_{i,t-1}$	0.023^{**}	0.03^{**}	0.029^{**}	0.03^{**}	0.03^{**}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$BidAsk_{i,t-1}$	-0.057	-0.055	-0.053	-0.056	-0.056
	(0.096)	(0.096)	(0.096)	(0.096)	(0.096)
$MCAP_{i,t-1}$	-0.196^{**}	-0.196^{**}	-0.196^{**}	-0.196^{**}	-0.196^{**}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.001	0.001	0.001	0.001	0.001
No obs	2,564,305	2,564,305	2,564,305	2,564,305	2,564,305