Do stock prices react to ESG sentiment?

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

Nov 2024

Abstract

We study the links between corporate ESG (Environmental, Social and Governance) issues and stock prices. We create ESG-related sentiment proxies using internet search and social media data (Google and Twitter). Using these innovations in ESG measures adds to current literature relying on ESG rankings, which are prone to misclassification. We find that companies with high ESG scores deliver low returns on average, but 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), or positive ESG sentiment (from Twitter). While our results cannot be explained by investor sentiment (Baker and Wurgler, 2006) alone, they are consistent with the equilibrium models of Pastor et al. (2021) and Pedersen et al. (2021)

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

*Kvam and Wankel from the Norwegian University of Science and Technology, Norway. Molnár from the Norwegian University of Science and Technology, Norway; University of Stavanger, Norway; Nicolaus Copernicus University in Toruń, Poland; and Prague University of Economics and Business, Czech Republic. Ødegaard from the University of Stavanger, Norway. 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. We are grateful for the comments of an anonymous referee.

Do stock prices react to ESG sentiment?

Abstract

We study the links between corporate ESG (Environmental, Social and Governance) issues and stock prices. We create ESG-related sentiment proxies using internet search and social media data (Google and Twitter). Using these innovations in ESG measures adds to current literature relying on ESG rankings, which are prone to misclassification. We find that companies with high ESG scores deliver low returns on average, but 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), or positive ESG sentiment (from Twitter). While our results cannot be explained by investor sentiment (Baker and Wurgler, 2006) alone, they are consistent with the equilibrium models of Pastor et al. (2021) and Pedersen et al. (2021)

1 Introduction

ESG (Environmental, Social and Governance) issues have in short order moved high on corporate agendas. The environmental aspect is primarily driven by the climate crisis, where governmental initiatives and regulation provide both opportunities and risks for corporations. Social and governance aspects are however also important. One example is the Nasdaq exchange's 2021 introduction of a diverse board as a listing requirement.

The question of whether corporate ESG characteristics affect stock prices is the subject of a by now large research literature.[1] This literature primarily uses ESG rankings as the explanatory variable. We add to this literature by linking *innovations* in ESG information to short-term stock price reactions.

Our research can be motivated by (at least) two theoretical approaches. First, from models where ESG characteristics are priced.[2] In such models innovations to ESG information will lead investors to update stock prices. Second, by looking at stock price reactions to ESG information through the lens of behavioral finance's investor sentiment analysis (Baker and Wurgler, 2006). To measure time varying ESG news, we use data from Internet search and social media to construct indices of ESG attention. These indices can be interpreted as proxying *Investor ESG sentiment*, and placed into a similar framework.

Our analysis can alternatively be motivated as providing information relevant for understanding whether ESG is related to *risk*. There is evidence that ESG aspects of a firm affects stock return probability distributions. For example high quality ESG firms seem to be more resilient in crashes,[3] which leads us to consider volatility, and questions such as how adverse events affect uncertainty and concerns about the environment.

In our analysis we look at short term (daily or weekly) stock returns, and relate them to a measure of ESG news, controlling for ESG level and other characteristics. To measure time

[1] See e.g. Hong and Shore (2023) for a summary.
[2] See e.g. Pástor et al. (2021) and Pedersen et al. (2021).
[3] For example the 2008 financial crisis (Lins et al., 2017) and the Covid crisis (Albuquerque et al., 2020).

varying ESG news, we primarily use data from Internet search and Social media, i.e. Google Search and Twitter. Google search data are used to construct company-level measures of public interest. People are likely to be searching for information about a company when the company is experiencing media interest or controversies. Google search statistics can also be used to gauge general public interest in ESG-related topics. Google search data does however not allow us to distinguish *sentiment*. To construct such measures we use data from Twitter. Using a number of keywords that are related to ESG, such as social responsibility, climate change, corporate governance, etc., we can measure the extent of public interest in a topic, and, more interestingly, the degree to which the tweets are positive or negative can be used to evaluate whether the twitter-sphere is positive or negative to either ESG in general, or to specific ESG-related topics. This last measure we consider a measure of ESG sentiment.

Using these news-based measures of ESG interest is a useful addition to the current research literature linking ESG rankings and stock prices/returns. A weakness of much of the current literature is that it relies on ESG ranking providers. It is by now acknowledged that there is widespread disagreement in the resulting rankings (Berg et al., 2022; Christensen et al., 2021). Using news-based data avoids the reliance on a weighting mechanism in the construction of ESG indices.

Our chief finding is that short-term stock returns in general are declining in ESG quality, but in the periods of ESG interest identified using our attention proxies, stock returns are higher for higher-quality ESG firms. We will show that this pattern is consistent with an ESG pricing model where high quality ESG firms have lower returns on average. The pattern is however not consistent with an investor sentiment model of the Baker and Wurgler (2006) type, as we find that when the market has a positive view of ESG, stock prices increase. Or, optimism is increasing in ESG. But this is not consistent with the average negative relation between ESG quality and average returns.

In a further 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. Our results using 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.

The rest of this study is structured as follows. We first, in section 2, provide background, develop the hypotheses, and place our investigations relative to similar research. In section 3 we explain our methods and present the data. Section 4 provides the results, before we conclude by relating the results to the implications for theoretical models.

2 Literature and hypotheses

Our analysis will look at stock price reactions to ESG *news*. To develop our research questions we find it useful to start with discussing the more general issue of whether ESG concerns affect stock prices (and returns).

2.1 ESG as a priced risk factor

One possible answer to this question is that ESG represent a systematic risk factor (Edmans, 2023). The challenge lies in identifying what is driving this factor (Lioui and Tarelli, 2022). For example, Bolton and Kacperczyk (2021) argues that carbon risk is priced. But, as argued by Cornell (2021), the jury is still out in terms of whether risk factors are a sufficient explanation.

A related issue is discussed in Avramov et al. (2022a), who 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. If we identify times with increased ESG attention, we can expect companies' ESG evaluations to become more precise, and thus affect returns.

2.2 Does ESG matter beyond cashflows?

Much of the ESG-related research literature however argues that the ESG characteristics of a firm affect stock prices beyond their effects through corporate cashflows, which means that this will not be captured by a risk factor.

Theoretically, there are two groups of explanations employed to make this argument, pecuniary and non-pecuniary views. The pecuniary view, or "doing well by doing good," argues that stock prices do not fully incorporate the consequences of future sustainability shocks, i.e. it is a mispricing argument, as in the short-termism literature (Stein, 1989). With this view, over time more responsible (higher quality ESG) firms will do better, and there will be a return premium associated with ESG. Under a non-pecuniary view investors have preferences over both the monetary return from an investment and that investment's ESG characteristics. In equilibrium, such preferences will support lower returns for firms with superior ESG ranking.[4]

There is a voluminous empirical literature investigating this proposed link between corporate ESG ranking and corporate performance.[5] While the literature has issues with measurement of ESG,[6] the majority of studies support a non-pecuniary view, where higher quality ESG firms have lower returns.

Note however that this literature is concerned with the overall ESG quality of a firm, what can be viewed as a ESG *level* effect. Our research is concerned with *innovations* to ESG quality, in the form of news and social media corporate mentions.

[4]Pástor et al. (2021) Pedersen et al. (2021) are examples of models of this tradeoff.

[5]For general surveys of this empirical literature see Kräussl et al. (2023), Atz et al. (2023). The surveys by Starks (2023) and Hong and Shore (2023) are more concentrated on sustainable finance.

[6]There is substantial disagreement in ESG rankings across providers of ESG scores. 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.

In the context of the static models above, one possible effect of such innovations can be to induce changes to investor preferences. This type of argument is made by Cornell (2021), who views high returns for ESG firms as a transitory phenomenon due to changing preferences. In a dynamic equilibrium model, Avramov et al. (2022b) show similar results, ESG preference shocks has return effects.

Alternatively one can view such innovations as updates of information available to investors. In a model where investors value ESG beyond their cash flow consequences, 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).

2.3 Investor Sentiment analysis

Investor Sentiment analysis is an approach in behavioral finance where stock prices can deviate from fully rational prices due to limits to arbitrage. Baker and Wurgler (2007) and Zhou (2018) provides introductions to this literature. Investor sentiment is beliefs about future cash flows not justified by current facts. If for example the sentiment is optimistic, it will lead to excess demand, increasing prices. While rational investors will trade against this, uncertainty and limits to arbitrage will limit the degree to which these counterforces work, and prices are too high. In the crossection there is variation in the ability to arbitrage. For example, illiquid and small stocks are harder to short.

Empirical analysis of investor sentiment typically construct measures of aggregate investor sentiment, and link them to stock returns. Baker and Wurgler (2007), for example, include investors surveys, investor mood, retail trader activity, trading volume/liquidity, and option implied volatility in their list of common mood proxies. In our research we posit ESG as a separate source of sentiment (*ESG sentiment*), construct measures of media attention to ESG, and investigate whether these measures are linked to stock returns.

Confusingly, the term "sentiment analysis" is also used with a different meaning in the research literature. In computer science it refers to methods for classifying the polarity of a text, determining whether the tone of the text is positive, negative, or neutral. These methods are employed in our work. To distinguish the two, we will refer to the behavioral finance analysis as "Investor sentiment."

2.4 Risk Management and Hedging

No matter whether the source of a link between ESG and stock prices is systematic or unsystematic, it has implication for risk management, which means it is useful to understand how ESG properties of stocks affect statistical properties of stock returns, such as volatility. For example, high quality ESG stocks seem to hedge against crises and potentially climate risks.[7]

[7] 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).

2.5 Hypotheses

Our paper is concerned with innovations in corporate ESG information. To construct proxies for *ESG news* we employ Internet data at either the company level or economy-wide. We regress short term (daily or weekly) stock returns on these measures of *ESG news*. In the regressions we include a number of additional variables. For one, we include a proxy for ESG quality (*ESG level*) in the analysis to condition the ESG news on the current ESG opinion. We also consider a number of other explanatory variables.

Generically, we can summarize the regression formulation as

$$r_{it} = f(ESG\ news_{it}, ESG\ level_{it}, \mathbf{X}_{it}),$$

where r_{it} is the stock returns for stock i in period t, $ESG\ news_{it}$ the measure using Internet data, $ESG\ level_{it}$ a measure of the ESG ranking of the firm, and $\mathbf{X}_{it}$ a vector of alternative factors relevant for short-term stock returns.[8]

The additional factors employed in the regressions are motivated from the investor sentiment literature. In that literature, the level of mispricing varies with the difficulty to value and the difficulty to arbitrage a given stock. Valuation difficulty increases in volatility. We therefore consider a measure of market variability, the VIX measure of implied market volatility (Whaley, 2000). Less liquid stocks are harder to arbitrage due to the risk of predatory trading (Brunnermeier and Pedersen, 2005). We therefore include measures of stock liquidity and stock size (market capitalization).

Let us now discuss the questions we investigate. We concentrate on periods with innovations in ESG information. How do we expect stock prices to react? Let us interpret the ESG information as updates to investor information. In a model where ESG is priced, prices will move to reflect the updated information. In the most common case, where expected returns are decreasing in ESG quality, positive ESG news will increase stock prices (higher short term returns), to reflect the lower expected returns. From an investor sentiment model standpoint, the predictions depend on how investor ESG sentiment is reflected in stock prices. If positive investor ESG sentiment lead to optimism, we expect positive ESG news to lead to higher stock prices (positive short term returns). To distinguish these two hypotheses we can look at the link to ESG levels.

In our discussion so far we have not distinguished the various components of ESG. But it is clearly interesting to ask if any effects we identify differ between E, S or G measures. Our analysis will therefore involve proxies broken down on each of these components.

[8] The reader may react to the apparent lack of risk adjustment in this formulation. We have in fact also tested the presented relationships using abnormal returns, estimated as residuals of a Fama-French (Fama and French, 1995) three-factor model, as the dependent variable. This produces similar results, and the conclusions drawn from using return as dependent variable remain unchanged. For ease of exposition we choose to only present the simpler formulation.

2.6 Directly comparable literature

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. In one of their analyses, Pástor et al. (2022) constructs a measure of climate concern, and link it to monthly returns.

Ballinari and Mahmoud (2022) construct measures of sentiment for sustainability from social media and link it to short-term stock returns, but is more concerned with predictability. Ardia et al. (2023) 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 (2020) and Serafeim and Yoon (2021) works with a short-term aggregation of ESG news, TruValueLabs, but do link it with short term stock returns. Their focus is different, though, as it is more concerned with differences in ESG rankings.

In Choi et al. (2020) people revise their beliefs about climate change when experiencing warmer than usual temperatures, which does have some similarities with our research

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.

Finally, Yu et al. (2023) also construct measures of ESG news-based sentiment, but use it to investigate stock price crash risk. Audrino et al. (2020) do a similar construction, but their focus is on predicting volatility[9]

2.7 Reactions to negative ESG news

We note that our research is distinct from investigations of corporate reactions to negative ESG news, which are more concerned with analysis in event time, such as Gantchev et al. (2022), who ask whether corporations will change their E&S (environmental & social) profile

[9] 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.

following negative E&S news (using the RepRisk database), or Duan et al. (2023), who ask whether firm *customers* react to negative ESG news.

Related to this type of investigation is analysis of *divestment* of stocks from institutional portfolios, which find that there is a negative reaction when stocks are divested for ESG-related reasons.[10]

3 Data and Methods

3.1 Company sample

We use data for US companies listed at either NYSE or NASDAQ. 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.

3.2 Estimating ESG news using social media data

Our measures of ESG news uses data from Internet search and social media. Let us start with the search data.

3.2.1 Google search volume

To measure public attention to companies and ESG topics we employ search volumes on Google, the world's most used search engine (Statista, 2021). Terms submitted to search engines reflect people's needs, wants, interests and concerns (Ettredge et al., 2005). Google search volumes have therefore been studied in a variety of settings.[11]

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.[12]

Search Volumes on Companies We use search volumes on company names to capture public attention to individual companies. We prefer company names to tickers, as many tickers are

[10]See for example the analyses of the divestments of the Norwegian "Oil Fund" in Atta-Darkua (2022), Nguyen et al. (2024) and Berle et al. (2024).

[11]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).

[12]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).

common abbreviations. Additionally, 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 frequencies 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, we choose a different approach than that used for ESG topics. 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 indexes weeks. If the SVI for a given time period is zero, $\log(SVI_{t,comp})$ is set to zero. The Abnormal SVI (AbSVI) measure is thus calculated as:

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

Search Volumes on ESG Topics We want to investigate separately the components of ESG, and therefore calculate separate search volume indices on ESG, environmental, social and governance topics.[13] 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.

These topic search volume indices (*SVI*) are constructed using 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 to Da et al. (2011), the *SVI* series are detrended using equation (2). Here t denotes days. The search volumes over the weekend are included on the first trading day of the following week. If the *SVI* for a given time period is zero, $\log(SVI_t)$ is set to zero.

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

3.2.2 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. To implement our measures, public English tweets containing the words "climate change," "corporate governance,"

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

"ESG," "social responsibility" or "sustainability" are scraped from Twitter. We exclude the tweets that satisfy either of the following:

- Tweets with identical content by the same user on the same day, disregarding hyperlinks. These tweets are usually spam.
- Tweets containing 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 using the formulation in 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.

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

This abnormal volume of tweets, AbTV, is employed as a measure of ESG concern. Table 1 presents the correlation between the five keywords' abnormal Twitter volume.

Sentiment Analysis Let us now discuss the information concept of sentiment analysis (which is different from the investor sentiment concept discussed earlier). 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). Social media is viewed as a representation of the public sentiment and opinion about current events (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.[14]

We therefore analyze tweets using sentiment analysis to capture the public mood about ESG. 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 for the categorization. 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, analyzes the content based on the word pattern in each tweet, and has been trained

[14]See e.g. (Go et al., 2009; Agarwal et al., 2011; Kouloumpis et al., 2011; Wang et al., 2012; Severyn and Moschitti, 2015).

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 2 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 3. 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:

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

Here *sentiment* represents either positive $(+)$ or negative $(-)$ sentiment, and t indexes date.

We finally create a *ESG 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 ESG related mood:

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

3.3 Company ESG Scores

To measure company ESG rankings we use Refinitiv Eikon scores. This is to ensure consistency with the ESG search volumes on ESG topics discussed above, which uses categorizations from Refinitiv. We remove companies without ESG data. Our final sample consists of 2030 companies, where 1139 are listed on NASDAQ and 891 on NYSE.[15]

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.[16] Table 4 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).

3.4 Stock 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. To represent the state of VIX we use the deviation from the previous one year's median, $AbVIX$:

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

We additionally use a number of market measures at the individual stock level: trading volume, liquidity and firm size.

Using a similar approach to Campbell et al. (1993) we calculate stock i's abnormal trading volume $AbVolume_{it}$ as

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

where VOL_i is either the daily or the weekly trading volume for stock i. We let $n = 252$ for daily volume or $n = 52$ for weekly volume. 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. A weekly spread is constructed as the average of the spreads over a given week. We finally control for firm size using the market capitalization ($MCAP_{it}$).[17]

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

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

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

4 Results

We start by investigating how the *level* of company ESG (ESG ranking), 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.

4.1 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 as a baseline before we look at innovations in ESG information.

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.[18]

As discussed earlier, the most common finding of studies explaining returns with ESG is a negative relationship. But these studies are usually done using monthly or even lower return frequencies. Here we are using high frequency (daily) returns, and still find highly significant (negative) coefficient estimates for all of the E, S and G sub-indices, as well as the total ESG index.

We next turn to the estimations of prime interest in this paper, where we add measures of innovations in ESG interest to the ESG level.

4.2 ESG concerns at the company level

We first analyse our measure of attention to individual companies measured using abnormal Google Search Volume on the company ($AbSVI_{it}$). 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 reduce noise in the public view of the company's ESG profile. This is similar to the argument of Avramov et al. (2022a) about variability of ESG ranking, and the effect of increases in precision of ESG ranking. With this argument, 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.

[18]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 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.

Table 6 shows the results. The Google Search Volume at the company level is available at a weekly frequency. This leads to a timing issue. We don't know when during a week the social media attention spikes, it could be toward the end of the week, or even 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 timing issues however leads us to concentrate on the lagged (predictive) regression in panel B. These next-week results have significantly positive coefficients on all ESG-related variables. Thus, better ESG firms' stock prices increase.

4.3 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.

4.3.1 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 $AbSVI$ without 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.

4.3.2 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. Using Twitter data also let us improve on the Google analysis in several ways. In this subsection we use the fact that we can look at individual aspects of ESG by looking at separate keywords in tweets. In the next subsection we will use sentiment analysis to investigate the *direction* of ESG sentiment.

To decompose ESG we use the five keywords "climate change," "corporate governance," "ESG," "social responsibility" and "sustainability." 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, ask whether it explains 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 is 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. The problem may be that these keywords are relatively narrow, and each of the various keyword searches have a low number of observations relative to the total.

4.3.3 Twitter mood and ESG

We instead turn to the case where we can look at the *direction* of information, whether the market is positive or negative to ESG. This is the ESG *Mood* variable constructed using sentiment analyis on the Tweets. Note that this variable is the difference between positive and negative tweets. A high number means that the market is positive to ESG issues. In this analysis we have the same timing issues as before. We therefore look at this both in terms of contemporaneous (same day) analysis in Table 9 and next day (forecasting) analysis in Table 10.

Let us first discuss the contemporaneous results in Table 9, showing 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. The results are somewhat mixed.

Model (1) in all five subtables of Table 9 show that a negative mood on Twitter, on average, is associated with higher stock returns. The impact of Twitter mood on stock returns is dependent on ESG, social and governance scores for the keywords “corporate governance,” “ESG,” “social responsibility” and “sustainability.” Companies with high scores generate higher returns when the mood related to these words is more negative.

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 sub-tables 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” sub-table. 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” sub-table.

As before we emphasize the forecasting results, as these are less prone to issues with timing. The results in Table 10 show analysis forecasting next-day returns. In all cases we find a highly significant and positive coefficient on the ESG variables when interacted with the previous day's ESG *Mood*. Stock prices increase on good ESG news. Note that these results are consistent with the results on indivial company Google searches in section 4.2, where also we had a positive coefficent. In that section we had some question as to the tenor of the news. The results using Mood confirm that it seems like good ESG news lead to increased stock prices.

4.3.4 ESG, volatility, and general uncertainty in the economy

We now turn to a somewhat different angle to ESG. The analysis is motivated by the ESG 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.

In investor sentiment analysis measures of market volatility, such as VIX, are often used as proxies for market sentiment. The question is whether ESG offer additional protection against uncertainty when we account for this market sentiment. To test this 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).

Our interest is however centered on the interaction terms with ESG, environmental, social and governance scores. In these regressions timing may be less of an issue, the VIX is a market price, but we still look at both contemporaneous and next day regressions. In the contemporaneous estimates we find that all coefficients intereacted with ESG are significantly positive. Companies with high ESG scores are associated with higher returns when market uncertainty is abnormally high. In the next day regression only the score on the environmental (E) index is significant (although they are all positive). This may be due to issues of climate change may be of particular concern.[19]

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 stock returns increase for firms with a high ESG ranking.

[19] 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.

5 Conclusion

The research questions in this paper concern how corporate ESG issues affect stock prices. There are two important features providing the novelty of our results. First, we use data from social media to capture dynamics in ESG information, *ESG news*. Looking at changes allow us to divorce our results from most of the relevant literature, which links ESG ratings (levels) to corporate performance. These ratings have been shown to vary substantially across rating providers. To ask whether media ESG coverage of a corporation, or the economy, is more intense, do not rely on the weighting choices going into an ESG ranking. Second, we use high frequency stock price changes (daily or weekly), instead of the lower frequency observations used in most other research.

Our clearest result is that times of heighened ESG interest (either at the company level or economy-wide) is associated with increases in stock prices. To make this point we mainly rely on forecasting regressions where ESG news forecast next day or next week returns. We additionally do an analysis where we link short term returns to a measure of ESG ranking (Refinitiv ESG scores), and find that returns are decreasing in ESG ranking.

These results have interesting implications when taken to the two theoretical approaches we discussed earlier, ESG being priced, and Investor Sentiment. First, these results are consistent with a pricing model where high quality ESG companies on average have lower returns, such as the Pástor et al. (2021) or Pedersen et al. (2021) models. In these models a group of investors is willing to forgo returns because they are compensated with ESG. In such a case, when ESG positive news for a company arrives, these investors will increase their demand for that company, increasing prices, leading to higher short term return (and lower long term returns).

Second, these results are *not* consistent with the Baker and Wurgler (2007) type of model of Investor ESG Sentiment. To see this, start with our result that stock prices increase with ESG attention. In particular, in one of these analyses, we constructed a *ESG mood* variable, which identified periods with good news. We found that stock prices were increasing in the *ESG mood* variable, which implies that *optimism* in an Investor ESG Sentiment model is increasing in ESG. But such an optimism do not square with the estimated negative relation between ESG level and stock returns, which should be positive if Investor Sentiment is increasing with ESG quality.

We view this input to the debate on how ESG affects stock prices as the most important contribution from our analysis, but we do make another interesting observation. Our result that short-term returns is higher for better quality ESG stocks means that ESG properties may be important for hedging short term shocks, which have implications for risk management. But for it to be important, ESG must give additional information to existing measures. Our final set of analyses therefore link estimates of the level of uncertainty in the economy (the VIX index) to our measures of ESG concerns. We find that ESG properties of a company is important for returns beyond the effect of uncertanty proxied by the VIX. Thus, the resiliency of high ESG ranked firms is a general feature of episodes of high economy-wide volatility.

References

Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca J Passonneau. Sentiment analysis of twitter data. In *Proceedings of the workshop on language in social media (LSM 2011)*, pages 30–38, 2011.

Rui Albuquerque, Yrjo Koskinen, Shuai Yang, and Chendi Zhang. Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash. *The Review of Corporate Finance Studies*, 9(3):593–621, 07 2020. doi:10.1093/rcfs/cfaa011.

David Ardia, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht. Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632, 2023. doi:10.1287/mnsc.2022.4636.

Vaska Atta-Darkua. Corporate ethical behaviours and firm equity value and ownership: Evidence from the GPFG's ethical exclusions. Available at SSRN, November 2022.

Ulrich Atz, Tracy Van Holt, Zongyuan Zoe Liu, and Christopher C Bruno. Does sustainability generate better financial performance? Review, meta-analysis, and propositions. *Journal of Sustainable Finance & Investment*, 13(1):802–825, 2023.

Francesco Audrino, Fabio Sigrist, and Daniele Ballinari. The impact of sentiment and attention measures on stock market volatility. *International Journal of Forecasting*, 36(2):334–357, 2020. doi:10.1016/j.ijforecast.2019.05.010.

Doron Avramov, Si Cheng, Abraham Lioui, and Andrea Tarelli. Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, 145(2, Part B): 642–664, 2022a. doi:10.1016/j.jfineco.2021.09.009.

Doron Avramov, Abraham Lioui, Yang Liu, and Andrea Tarelli. Dynamic ESG equilibrium. SSRN, November 2022b.

Malcolm Baker and Jeffrey Wurgler. Investor sentiment and the cross-section of stock returns. *Journal of Finance*, 61(4):1645–81, 2006.

Malcolm Baker and Jeffrey Wurgler. Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–151, 2007.

Scott Baker and Andrey Fradkin. *What Drives Job Search?: Evidence from Google Search Data*. Stanford Inst. for Economic Policy Research, 2011.

Daniele Ballinari and Ola Mahmoud. More than chatter: An index of sustinability sentiment. Working Paper, SSRN, May 2022.

Prithviraj S Banerjee, James S Doran, and David R Peterson. Implied volatility and future portfolio returns. *Journal of Banking & Finance*, 31(10):3183–3199, 2007.

Florian Berg, Julian F Kölbel, Anna Pavlova, and Roberto Rigobon. ESG confusion and stock returns: Tackling the problem of noise. SSRN Working Paper, 2021.

Florian Berg, Julian F Kölbel, and Roberto Rigobon. Aggregate confusion: The divergence of ESG ratings. SSRN Working Paper, January 2022.

Erika Berle, Wanwei (Angela) He, and Bernt Arne Ødegaard. The expected returns of ESG excluded stocks. Shocks to cost of capital? Evidence from the worlds largest fund. Working Paper, University of Stavanger, April 2024.

Laurens Bijl, Glenn Kringhaug, Peter Molnár, and Eirik Sandvik. Google searches and stock returns. *International Review of Financial Analysis*, 45:150–156, 2016. doi:10.1016/j.irfa.2016.03.015.

Patrick Bolton and Marcin Kacperczyk. Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549, 2021. doi:10.1016/j.jfineco.2021.05.008.

Markus K Brunnermeier and Lasse Heje Pedersen. Predatory trading. *Journal of Finance*, 60(4):1825–1863, 2005.

John Y Campbell, Sanford J Grossman, and Jiang Wang. Trading volume and serial correlation in stock returns. *The Quarterly Journal of Economics*, 108(4):905–939, 1993.

Herman Anthony Carneiro and Eleftherios Mylonakis. Google trends: A web-based tool for real-time surveillance of disease outbreaks. *Clinical Infectious Diseases*, 49(10):1557–1564, 2009.

Yan Carrière-Swallow and Felipe Labbé. Nowcasting with Google Trends in an Emerging market. *Journal of Forecasting*, 32(4):289–298, 2013. doi:10.1002/for.1252.

Tao Chen. Investor attention and global stock returns. *Journal of Behavioral Finance*, 18(3):358–372, 2017.

Yao Chen, Alok Kumar, and Chendi Zhang. Dynamic ESG preferences and asset prices. Working paper, SSRN, March 2020.

Darwin Choi, Zhenyu Gao, and Wenxi Jiang. Attention to global warming. *The Review of Financial Studies*, 33 (3):1112–1145, 2020.

Hyunyoung Choi and Hal Varian. Predicting the present with Google trends. *Economic Record*, 88(s1):2–9, 2012. doi:10.1111/j.1475-4932.2012.00809.x.

Dane M. Christensen, George Serafeim, and Anywhere Sikochi. Why is corporate virtue in the eye of the beholder? The case of ESG ratings. *The Accounting Review*, February 2021. doi:10.2308/TAR-2019-0506.

Bradford Cornell. ESG preferences, risk and return. *European Financial Management*, 27(1):12–19, 2021. doi:10.1111/eufm.12295.

Zhi Da, Joseph Engelberg, and Pengjie Gao. In search of attention. *The Journal of Finance*, 66(5):1461–1499, 2011.

Ruben Joris Pieter de Groot. ESG and stock market performance: The impact of Twitter sentiment. Master's thesis, University of Groningen, 2020.

François Derrien, Philipp Krueger, Augustin Landier, and Tianhao Yao. How do ESG incidents affect firm value? Available at SSRN 3903274, 2021.

Marian Alexander Dietzel. Sentiment-based predictions of housing market turning points with Google trends. *International Journal of Housing Markets and Analysis*, 2016.

Elroy Dimson, Paul Marsh, and Mike Staunton. Divergent ESG ratings. *The Journal of Portfolio Management*, 47(1):75–87, 2020.

Justin Doldersum. Is it worth the risk? – The effect of Twitter sentiment on expected returns and the moderating role of Twitter sentiment in the relationship between ESG and expected returns. Master's thesis, University of Groningen, June 2021.

Tinghua Duan, Frank Weikai Li, and Roni Michaely. Customer reaction to corporate ESG performance: Evidence from store visits. Working Paper, February 2023.

Alex Edmans. The end of esg. *Financial Management*, 52 (1):3–17, 2023. doi:10.1111/fima.12413.

Michael Ettredge, John Gerdes, and Gilbert Karuga. Using web-based search data to predict macroeconomic statistics. *Communications of the ACM*, 48(11):87–92, 2005.

Eugene F Fama and Kenneth R French. Size and book-to-market factors in earnings and returns. *Journal of Finance*, 50(1):131–56, March 1995.

Nickolay Gantchev, Mariassunta Giannetti, and Rachel Li. Does Money Talk? Divestitures and Corporate Environmental and Social Policies. *Review of Finance*, 26(6):1469–1508, 05 2022. doi:10.1093/rof/rfac029.

Jeremy Ginsberg, Matthew H Mohebbi, Rajan S Patel, Lynnette Brammer, Mark S Smolinski, and Larry Brilliant. Detecting influenza epidemics using search engine query data. *Nature*, 457(7232):1012–1014, 2009.

Pierre Giot. Relationships between implied volatility indexes and stock index returns. *The Journal of Portfolio Management*, 31(3):92–100, 2005.

Alec Go, Lei Huang, and Richa Bhayani. Twitter sentiment analysis. *Entropy*, 17:252, 2009.

Google. FAQ about Google Trends data - Trends help, 2021.

Axel Groß-Klußmann, Stephan König, and Markus Ebner. Buzzwords build momentum: Global financial twitter sentiment and the aggregate stock market. *Expert Systems with Applications*, 136:171–186, 2019.

A. Hasan, S. Moin, A. Karim, and S. Shamshirband. Machine learning-based sentiment analysis for twitter accounts. *Mathematical and Computational Applications*, 23(1), 2018. doi:10.3390/mca23010011.

Harrison G Hong and Edward P Shore. Corporate social responsibility. *Annual Review of Financial Economics*, 2023. doi:10.2139/ssrn.4267476.

C. Hutto and E. Gilbert. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 8, 2014.

Efthymios Kouloumpis, Theresa Wilson, and Johanna Moore. Twitter sentiment analysis: The good the bad and the omg! In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 5, 2011.

Roman Kräussl, Tobi Oladiran, and Denitsa Stefanova. A review on esg investing: Investors' expectations, beliefs and perceptions. *Journal of Economic Surveys*, 2023. doi:10.1111/joes.12599.

Rachmawan Adi Laksono, Kelly Rossa Sungkono, Riyanarto Sarno, and Cahyaningtyas Sekar Wahyuni. Sentiment analysis of restaurant customer reviews on tripadvisor using naïve bayes. In *2019 12th International Conference on Information Communication Technology and System (ICTS)*, pages 49–54, 2019. doi:10.1109/ICTS.2019.8850982.

Karl V. Lins, Henri Servaes, and Ane Tamayo. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4):1785–1824, 2017. doi:10.1111/jofi.12505.

Abraham Lioui and Andrea Tarelli. Chasing the ESG factor. *Journal of Banking and Finance*, February 2022. doi:10.2139/ssrn.3878314.

Bing Liu. Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, 5(1): 1–167, 2012.

Walaa Medhat, Ahmed Hassan, and Hoda Korashy. Sentiment analysis algorithms and applications: A survey. *Ain Shams engineering journal*, 5(4):1093–1113, 2014.

Tetsuya Nasukawa and Jeonghee Yi. Sentiment analysis: capturing favorability using natural language processing. In *Proceedings of the 2nd international conference on Knowledge capture*, pages 70–77, 2003.

Le T. P. Nghiem, Sarah K. Papworth, Felix K. S. Lim, and Luis R. Carrasco. Analysis of the capacity of Google trends to measure interest in conservation topics and the role of online news. *PLoS ONE*, 11(3):1–12, 2016. doi:10.1371/journal.pone.0152802.

Quynh Trang Nguyen, Snorre Lindset, Sondre Hansen Eriksen, and Marie Skara. Can an influential and responsible investor indeed be influential through responsible investments? Evidence from a $1 trillion fund. *International Review of Economics & Finance*, 89: 1120–1135, 2024. doi:10.1016/j.iref.2023.07.106.

Venkata Sasank Pagolu, Kamal Nayan Reddy, Ganapati Panda, and Babita Majhi. Sentiment analysis of twitter data for predicting stock market movements. In *2016 International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES)*, pages 1345–1350, 2016. doi:10.1109/SCOPES.2016.7955659.

Lúboš Pástor, Robert F Stambaugh, and Lucian A Taylor. Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571, 2021. doi:10.1016/j.jfineco.2020.12.011.

Lúboš Pástor, Robert F Stambaugh, and Lucian A Taylor. Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424, 2022. doi:10.1016/j.jfineco.2022.07.007.

Lasse Heje Pedersen, Shaun Fitzgibbons, and Lukasz Pomorski. Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, 142(2):572–597, 2021. doi:10.1016/j.jfineco.2020.11.001.

Camille Pelat, Clement Turbelin, Avner Bar-Hen, Antoine Flahault, and Alain-Jacques Valleron. More diseases tracked by using Google trends. *Emerging Infectious Diseases*, 15(8):1327, 2009.

Tobias Preis, Helen Susannah Moat, and H Eugene Stanley. Quantifying trading behavior in financial markets using Google trends. *Scientific Reports*, 3, 04 2013. doi:10.1038/srep01684.

L'uboš Pástor and M Blair Vorsatz. Mutual Fund Performance and Flows during the COVID-19 Crisis. *The Review of Asset Pricing Studies*, 10(4):791–833, 09 2020. doi:10.1093/rapstu/raaa015.

Refinitiv. Environmental, Social and Governance (ESG) scores from Refinitiv, February 2021. URL `https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf`.

Caterina Santi. Investor climate sentiment and financial markets. Working paper, SSRN, September 2020.

George Serafeim. Public sentiment and the price of corporate sustainability. *Financial Analysts Journal*, 76(2): 26–46, 2020. doi:10.1080/0015198X.2020.1723390.

George Serafeim and Aaron Yoon. Stock price reactions to ESG news: The role of ESG ratings and disagreement. *Review of Accounting Studies*, 2021. doi:10.2139/ssrn.3765217.

Aliaksei Severyn and Alessandro Moschitti. Twitter sentiment analysis with deep convolutional neural networks. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*, pages 959–962, 2015.

Laura T Starks. Presidential address: Sustainable finance and ESG issues – Value versus Values. *The Journal of Finance*, 2023. doi:10.1111/jofi.13255.

Statista. Worldwide desktop market share of leading search engines from january 2010 to february 2021, 2021.

Jeremy Stein. Overreactions in the options market. *Journal of Finance*, 44:1011–23, 1989.

Jesse Turkson. ESG investing in uncertainty: Analyzing the returns of ESG within various states of investor sentiment. Master's thesis, Haverford College, 2021.

Simeon Vosen and Torsten Schmidt. Forecasting private consumption: survey-based indicators vs. Google trends. *Journal of Forecasting*, 30(6):565–578, 2011. doi:10.1002/for.1213.

Hao Wang, Doğan Can, Abe Kazemzadeh, François Bar, and Shrikanth Narayanan. A system for real-time twitter sentiment analysis of 2012 us presidential election cycle. In *Proceedings of the ACL 2012 system demonstrations*, pages 115–120, 2012.

Robert E Whaley. The investor fear gauge. *The Journal of Portfolio Management*, 26(3):12–17, 2000.

Jin Boon Wong and Qin Zhang. Stock market reactions to adverse ESG disclosure via media channels. *The British Accounting Review*, 54(1):101045, 2022. doi:10.1016/j.bar.2021.101045.

Haixu Yu, Chuanyu Liang, Zhaohua Liu, and He Wang. News-based esg sentiment and stock price crash risk. *International Review of Financial Analysis*, 88:102646, 2023. doi:10.1016/j.irfa.2023.102646.

Guofu Zhou. Measuring investor sentiment. *Annual Review of Financial Economics*, 10:239–259, 2018.

Table 1: 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 $AbTV_t = \log(TV_t) - \log\left(Median(TV_{t-7}, TV_{t-14}, ..., TV_{t-364})\right)$, 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 2: 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 3: 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

		Flair		
		Positive	Negative	Total
VADER	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

		Flair		
		Positive	Negative	Total
TextBlob	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

		VADER			
		Positive	Neutral	Negative	Total
TextBlob	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 4: 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 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 today's volume and "normal" volume, as specified in equation (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 today's volume and "normal" volume, as specified in equation (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 today's volume and "normal" volume, as specified in equation (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 today's volume and "normal" volume, as specified in equation (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 today's volume and "normal" volume, as specified in equation (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

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

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 is 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 today's volume and "normal" volume, as specified in equation (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 today's volume and "normal" volume, as specified in equation (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: (Same day) 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: (Next day) 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