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

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Abstract

We investigate the link between stock returns and ESG (Environmental, Social and Governance) concerns. The ESG concerns are measured by ESG-related sentiment extracted from Google Trends and Twitter, and also by the VIX index. We find that higher ESG scores are associated with lower stock returns on average. However, companies with high ESG scores deliver high returns in times of ESG concerns. Our results are consistent with the implications of equilibrium models of Pastor et al. (2021) and Pedersen et al. (2021) about the ESG score and changes in ESG concerns (preferences or news).

Keywords: ESG investing; Social Media; Exclusion
JEL codes: G10; G12

Introduction

For investors, ESG (environmental, social and governance) concerns has in recent years moved to the forefront when making investment decisions. Institutional investors maintain long lists of companies excluded for ESG reasons, and the popularity of "responsible" mutual funds is growing apace.[1]

The key research questions driven by this "ESG investment revolution" concerns the equilibrium consequences for stock prices. When a large fraction of investors rule out the stocks of "bad" (in the ESG sense) companies from their investable universe, will these demand changes move the relative pricing of the "good" stocks versus the "bad"? In what directions?

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

These questions are asked in the context of theoretical models by e.g. Pástor et al. (2021) and Pedersen et al. (2021), who builds models where a subset of investors has preferences in “ESG dimensions” in addition to asset returns. For example, the Pástor et al. (2021) model has a clear prediction: With a subset of investors with “ESG preferences,” stocks with high ESG scores can sustain a lower asset return, as these investors are willing to forgo asset returns in lieu of the higher utility from owning “responsible” equities. The model has a second implication: When companies improve their ESG score, by for example increasing their sustainable credentials, or when there is a preference shift among investors, stock prices of high-quality ESG stocks will quickly react positively (driven by the increased demand for “Green” stocks).

In this paper we perform an investigation of the implications of these models. In particular we consider the second type of model implication, that stock prices will immediately react to ESG innovations. To that end we investigate short term (daily and weekly) US stock returns and use data from social media to identify periods with intense (economy- or company-level) focus on ESG.

Our findings can be summarized as follows. We start by regressing stock returns on measures of ESG quality alone (the “level” of ESG quality), and find a negative relationship between stock returns and general ESG quality (ie. lower returns on “good” ESG firms).

We move on to incorporate short-term data from social media into the analysis. In our second set of analyses we interact company-level measures (from Google search data) of ESG interest with returns. Here we find that high-quality ESG firms have superior returns in periods with ESG scrutiny of the company. In this context we consider both contemporaneous and lagged returns (predictability). These company-level results are consistent with price increases on “positive ESG news” at the company level.

Our final set of analyses looks at economy-wide variations in ESG concerns. We use both the degree of social media ESG concerns, measured using e.g. Twitter, and the level of uncertainty in the economy, proxied by the VIX index. These are periods where investors preferences are likely to change. For example, when climate-concerns increase, people will care more about the carbon footprint of companies. Similarly, during financial crises the hedging properties of “good” companies comes to the forefront.[2] We find that high-quality ESG firms have higher returns in periods of pessimism in the market (ie. a high level of the VIX, or a low Twitter mood on ESG).

The rest of this study is structured as follows. We first, in section 1, provide a background and place our investigations relative to similar research. In section 2 we explain

[2]This type of implications was crash-tested using the onset of the Covid pandemic in e.g. Albuquerque et al. (2020); Pástor and Vorsatz (2020), who showed that superior ESG stocks and funds performed relatively better.

our methods and present the data. Section 3 provides the results before we offer a short conclusion.

1 Research issue

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

This practitioner interest has been followed by academic investigations. Most of the academic work is empirical, looking for links between ESG characteristics and company performance. This literature has grown so quickly that a recent survey (Coqueret, 2021) lists 10 *meta* studies of the issue, the last of which (Whelan et al., 2021) surveyed over 1,000 studies produced in the period 2015–2020. There is no clear conclusion from these studies. While a majority finds a positive association between ESG quality and performance, there are also numerous studies with opposite conclusions.

A potential cause of this lack of agreement is the *measurement problem*. ESG – environment, social, governance – represent three different aspects of a company operations. From the investors point of view, it is desirable to come up with a single ESG ranking of stocks. To provide such rankings a whole advisory industry has materialized, with each advisor developing a distinct system of ESG scoring, choosing a set of measurements, which are weighted into numerical representations of ESG scores. Given the large number of choices involved in such procedures, it is no surprise that these scores disagree across providers (Dimson et al., 2020; Berg et al., 2022; Christensen et al., 2021).[3]

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

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

Much of the empirical work on ESG does not really discuss why the focus on ESG, and the removal of part of a stock's potential investors through exclusion, should induce differences in expected returns. Intuitively, exclusions should reduce the feasible set of investment portfolios, worsening the risk/return trade-off. Indeed, this kind of reasoning was behind some of the early empirical work on "sin" stocks (Hong and Kacperczyk, 2009), which found evidence of superior returns for industries typically excluded by ESG screens (tobacco, weapons).

We are however seeing an emergent theoretical literature on the equilibrium consequences of ESG concerns. Pástor et al. (2021) and Pedersen et al. (2021) are the best known examples. Key to these and related models is that the investors in the model have preferences over both the monetary return from an investment, and the investments' ESG characteristics. For example, investors can feel satisfaction in not supporting gun violence through ownership of gun manufacturers (negative screening). On the other hand, investors may want to support clean energy generation, and get an extra utility from investing in such energy companies.

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

Second, concerning dynamic short term innovations in stock prices. Times when ESG concerns "rise to the surface" will be associated with short term stock price reactions. For example, the media attention during the '21 Glasgow meeting on Climate Change may induce changes in people's preferences for investments in clean energy and similar attempts to reach the 2% temperature target. Another example concerns corporate actions that changes the firm's ESG profile. When Siemens in 2021 divested their oil and gas division, the "new" Siemens suddenly was a more climate-friendly corporation. We term such short term effects the result of "ESG concerns."[4]

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

[4] An alternative interpretation of these effects is provided by Cornell (2021), who views high returns for ESG firms as a transitory phenomenon due to changing preferences.

Before moving on to our results, let us discuss how our research relates to other studies. The distinguishing part of our research is the use of social media to identify time variation in ESG concerns, and linking this to stock returns.

Most of the empirical literature linking ESG to stock performance looks at longer-term, such as monthly, returns. The research linking short-term returns, ESG, and social media is more 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.

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

Santi (2020) has some similarities with our analysis, she looks at Social Media mentions (StockTwits posts), use it to identify periods of investor concern, and link it to stock returns. We however note that the analysis is specific to climate risks, and that she uses longer term stock returns than our analysis.[5]

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

2 Methods and Data

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

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

[5]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.

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

2.1 Company ESG Scores

To measure company ESG rankings we use Refinitiv Eikon scores. While there is a large number of alternative sources of ESG rankings, the Refinitiv ones are widely disseminated, which we view as important when we consider links to social media. We remove companies without ESG data. Our final sample consists of 2030 companies, whereby 1139 are listed on NASDAQ and 891 on NYSE.[6]

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.[7] Table 1 provides some descriptive statistics of the scores. We note that all the scores are positively correlated, but imperfectly so, with the Social (S) and Governance (G) scores the least correlated (0.37).

2.2 Social media data

2.2.1 Google search volume

We want to investigate public attention to companies and ESG topics. We measure this by search volumes on Google, the most used search engine in the world (Statista, 2021). Terms submitted to search engines reflect people's needs, wants, interests and concerns (Ettredge et al., 2005). Therefore, Google search volumes have been studied in a variety of settings. 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) and stock returns (Da et al., 2011; Joseph et al., 2011; Bijl et al., 2016). While Da et al. (2011) and Joseph et al. (2011) find that high Google search volumes predicts high future returns, Bijl et al. (2016) find that high Google search volumes predicts low future returns. Chen (2017) find that more searches for the Dow Jones Industrial Index (DJIA) is related to higher index returns.

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

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

Despite a variety of topics studied using Google search volumes, there is limited research on the dependency between attention to sustainability and stock returns.

Google search volume indices (SVIs) are obtained from Google Trends. The indices represent the relative popularity of a query within a specified time frame and a geographical range. The values lie within a range of 0 to 100, with 100 signifying the maximum search interest. Zero is by Google given to terms with low search volumes.[8] To create the search volume indices, Google Trends uses a sub-sample of all searches. Consequently, identical queries in Google Trends may produce results that are slightly different (Baker and Fradkin, 2011; Da et al., 2011; Carrière-Swallow and Labbé, 2013; Dietzel, 2016).

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

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

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

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

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

[8]For a detailed description of how Google estimates the indices, see Google (2021).
[9]The search terms included in each index can be found in the Internet Appendix.

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

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

2.2.2 Twitter

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

We also create a mood index, termed MOOD. The variable combines the amount of tweets per day labelled as positive, neutral and negative to give an indication of the overall mood:

$$MOOD = \frac{TV_t^{+} - TV_t^{-}}{TV_t} \tag{5}$$

2.3 Other market data

In the analysis we additionally employ the CBOE Volatility Index (VIX) as a measure of market-wide uncertainty. The VIX is a measure of the implied short-term volatility for the US stock market, calculated from option prices. VIX reflects investor uncertainty and is known as the "investor fear gauge" (Whaley, 2000). VIX spikes during crisis. Its highest level yet was reached during the recent COVID-19 pandemic. Such events are also reflected in the stock market, as stock returns are negatively correlated with implied market volatility (French et al., 1987; Sarwar, 2012). This relationship is found to be asymmetric, thus the stock market reacts more negatively to an increase in VIX than it reacts positively to a decline in VIX. Therefore, VIX is more a barometer of investors' fear of the downside than of the excitement in a market rally.

We consider two transformations for VIX. The first is the deviation from the previous one year's median, $AbVIX$:

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

The second transformation for VIX is the percentage deviation from previous day's VIX:

$$\Delta VIX_t = \frac{VIX_t - VIX_{t-1}}{VIX_{t-1}}. \tag{7}$$

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

$$AbVolume_{it} = \log(VOL_{it}) - \log(Median(VOL_{t-1}, VOL_{t-2}, ..., VOL_{t-n})) \tag{8}$$

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

Similarly, liquidity is found to significantly affect stock returns (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Datar et al., 1998). We proxy daily liquidity with the closing bid-ask spread, often called the quoted spread, calculated as the difference between the closing bid and ask prices divided by the price midpoint.:[10]

Finally, we control for firm size using the market capitalization ($MCAP$)[11]

3 Results

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

3.1 Relationship between ESG Scores and Stock Returns

We begin by evaluating the relationship between stock returns and the overall ESG score, as well as environmental, social and governance subscores. This establishes the general relationship between a company's sustainability level and its stock returns. The results

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

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

using OLS regressions are presented Panel A in Table 5. We also check these relationship using panel data regression with fixed effects presented in Panel B.

The results in Panel A show that all scores are significant in explaining stock returns. The companies with the highest scores experience the lowest returns. Thus, on average, sustainable companies deliver inferior returns. Panel B, with similar negative and significant relationships, verifies that these findings hold also when a panel data regression is used.

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.

3.2 ESG concerns at the company level

The Impact of Google Search Volume on Stock Returns In this section, we study the impact of public attention to individual companies and various sustainability topics, measured by Google search volumes. We first investigate how the abnormal Google search volumes on company names impact weekly stock returns and how this depends on the companies' ESG scores. Second, we investigate how the ESG, environmental, social and governance scores affect daily stock returns when the public show interest in sustainability topics. The four topics on sustainability; ESG, environmental, social and governance, are evaluated with their corresponding score. The aim is to evaluate whether companies with high scores generate higher returns when there is an increased level of attention to individual companies and sustainability.

Weekly Google Searches on Company Names Table 6 shows how daily Google search volumes on company names relate to stock returns the same week. Model (1) shows that there is 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. Similar results are found by Chen (2017), who studies Google search volumes on the Dow Jones Industrial Index (DJIA) and its returns. Furthermore, it can be seen in model (2), (3), (4) and (5) that weekly stock returns explained by search volumes on companies do not depend on ESG scores.

Next, we investigate if search volumes on company names can predict stock returns. The results are presented in Table 7. The results of model (1) indicate that search volumes for individual companies are significant in predicting stock returns. This result is consistent with the findings of Bijl et al. (2016). Model (2), (3), (4) and (5) show that the impact of Google search volumes on stock returns depend on the ESG, E, S and G scores. We find that companies with high scores across all ESG factors generate higher returns when they receive more attention. Thus, when investors pay attention to individual company information, they also seem pay attention to their sustainability level. Furthermore, we observe that stock returns explained by search volumes on companies are most impacted by the overall ESG score.

Daily Google Searches on ESG Topics We now investigate how attention to sustainability topics affect stock returns of sustainable companies the same day. The results are presented in Table 8. We observe in model (1), (3), (5) and (7) that, on average, more attention on ESG, environmental, social and governance topics affect stock returns negatively. Model (2), (4), (6) and (8) show that the impact of Google search volumes on stock returns depends on ESG, environmental and governance scores. When the attention on Google is high, companies with high scores generate higher returns. Conversely, when investor pay little attention to ESG, environmental and governance topics, companies with the lowest scores generate higher returns. Attention to social topics, however, does not seem to affect stock returns differently for companies with high or low social scores. Thus, increased attention to sustainability topics on Google is related to higher returns for the companies ranked highest on overall ESG, environmental and governance factors.

Next, we investigate if daily Google search volumes on ESG, environmental, social and governance topics predict stock returns. The results are presented in Table 9. The results show that increased attention to ESG, environmental, social and governance topics, observed in model (1), (3), (5) and (7) respectively, predicts higher returns following a day with high search volumes on these topics. As observed in model (2), (4), (6) and (8), stock returns predicted by search volumes on sustainability topics do not depend on ESG scores.

In this section, we have shown that sustainable companies generate higher returns when there is an increased level of attention to individual companies and ESG topics. Attention to social topics seems to be the least important for explaining stock returns.

3.3 Economy-wide concerns

3.3.1 The Impact of Twitter Volume and Sentiment on Stock Returns

We now investigate if engagement on Twitter about ESG topics is related to stock returns. We study tweets containing "climate change," "corporate governance," "ESG," "social responsibility" and "sustainability," and use them as measures of engagement on ESG topics. These keywords are related to different factors of ESG, and are thus studied in relation to their appropriate score(s). We use "climate change" as a measure of engagement on the environmental factor and "social responsibility" as a measure of engagement on the social factor. Both "corporate governance" and "social responsibility" are used as measures of engagement on the governance factor, as the latter word may also contain tweets on "corporate social responsibility." Additionally, all five keywords are used as measures of engagement on overall ESG. As observed in the data section, there is low correlation between the volume of tweets containing the different words. We therefore study all five keywords separately.

First, we evaluate whether the volume of tweets containing either of the five keywords explain stock returns of companies depending on their ESG scores. The aim of doing so, is to find out if companies with high scores generate higher returns when there is more buzz related to sustainability on Twitter. Second, we perform sentiment analysis on the content of each tweet to determine if positive or negative utterance is more important in explaining stock returns. We also combine the positive and negative volume of tweets to establish the overall mood. The mood related to ESG topics is used to explain and predict stock returns of companies, and to investigate how these relationships depend on companies' ESG scores.

Twitter Volume Table 10 shows how the daily volume of tweets for each keyword are related to stock return and how this depends on companies' ESG scores. Model (1) for each keyword indicate that there is no conclusive relationship between the amount of tweets and stock returns. More tweets about "sustainability," "climate change" and "corporate governance" affect stock returns negatively, while more tweets about "social responsibility" is positively related to stock returns. We find that the impact on stock returns of Twitter volume on "climate change" and "social responsibility" depend on the environmental score, and the ESG and governance score, respectively. More engagement on Twitter related to "climate change" seems to affect the stock returns of companies with high environmental score negatively, observed in model (3) of "climate change." In addition, companies with high ESG and governance score are slightly negatively affected by increased buzz related to "social responsibility" on Twitter, seen in model (2) and (4) of "social responsibility." In general, we observe that there are few significant relationships. Engagement itself seems to affect stock returns of companies with different ESG scores similarly. We therefore investigate if the sentiment of each tweet is important in explaining stock returns.

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

The subtables of Table 11 show the relationships between the daily sentiment on Twitter of each keyword and the stock returns of companies with different ESG, environmental, social and governance scores. As previously mentioned, each keyword is only studied in relation to the appropriate scores.

Model (1) in all five subtables of Table 11 show that a negative mood on Twitter, on average, is related to 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. 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 if the amount of positive or negative tweets has the most influence on stock returns. Our results in the subtables of Table 11 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 on the direction of this dependency. On one hand, a high amount of negative tweets related to "ESG" contributes positively to the returns of companies with high ESG score, presented in model (6) of the "ESG" subtable. On the other hand, a low amount of negative tweets related to "social responsibility" is associated with lower stock returns for high-ranked companies, as seen in model (10), (11) and (12) in the "social responsibility" subtable. Due to the lack of consistency between the separate Twitter sentiments and stock returns, we use the mood as the overall indicator of investor sentiment on Twitter.

Twitter Mood in Stock Return Prediction We now use the Twitter mood related to each keyword to evaluate if the mood can predict stock returns, and whether this depends on the ESG, environmental, social and governance scores. The results are presented in Table 12. We observe that the mood on Twitter for all keywords are significant in predicting stock returns. This is observed in model (1) for all keywords. However, the mood might predict both positive and negative returns, depending on the keyword studied. A positive mood related to "ESG" and "sustainability" predicts higher stock returns, while a negative mood related to "climate change," "social responsibility" and "corporate governance" predicts higher returns. When we investigate the impact of the mood on stock returns of companies with high and low scores, we find that a positive mood for all keywords predicts higher returns the following day for high-ranked companies. This relationship is opposite of what we found for the mood and stock returns of sustainable companies the same day. Presumably, this may occur as the behavior of investors are different for positive and negative sentiments. A positive sentiment increases the adoption of future goals, while a negative sentiment triggers a focus on immediate concerns (Liberman and Trope, 1998; Eyal et al., 2004; Bar-Anan et al., 2006; Fujita et al., 2006; Labroo and Patrick, 2009). Thus, an investor might be likely to invest in sustainable companies immediately when there is more public concern about sustainability. However, in the long run, the positive sentiment may influence investor to invest in sustainable companies due to a belief in long-term profitability. Accordingly, sustainable companies may generate higher daily returns when there is more negativity on Twitter related to sustainability, but on a longer term generate higher returns when there is more positivity.

In this section we have shown that companies with higher ESG scores generate higher returns on days where the mood on Twitter is negative. One day after, however, this is reversed, and companies with lower ESG scores achieve higher returns.

3.3.2 The Impact of VIX on Stock Returns

our final measure of investor concern is VIX, a measure of implied market volatility. We start by investigating how the deviation in VIX from its one year rolling median affects stock returns. We do this to evaluate whether the companies with high ESG scores generate superior returns in times of high market uncertainty. Subsequently, we study the relationship between stock returns and deviations in VIX from the previous day's VIX. The motivation for this is to investigate if sudden changes in investor fear, and not just the abnormal uncertainty level itself, affects stock returns of companies with high and low ESG scores differently.

Deviation in VIX from Its One Year Median Table 13 shows how the ESG, environmental, social and governance score explain stock returns when the deviation in VIX from its one year rolling median is high or low.

We observe that stock returns and deviation 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). Furthermore, when we investigate how this relationship depends on the ESG, environmental, social and governance scores in model (2), (3), (4) and (5) respectively, we find that the returns of companies with high scores across all factors are less sensitive to the market uncertainty. Companies with high scores generate higher returns, compared to those with lower scores, when market uncertainty is abnormally high, but not when market uncertainty is abnormally low. Thus, sustainable companies seem to be associated with less risk, and investors pay a premium for these stocks in times of high market uncertainty. The lower risk of sustainable companies is consistent with the findings of Fulton et al. (2012) and De and Clayman (2015). We observe that when uncertainty is high, the differences in stock returns between high and low scored companies are greatest for the ESG and governance score.

We next investigate whether the deviations in VIX from its one year rolling median can predict stock returns the following day. The results are presented in Table 14. The results show that the relationship between stock returns and deviations in VIX from its one year rolling median the previous day is significant and positive. This is consistent with the findings of Giot (2005), who finds the same positive relationship for 20 days forward-looking returns. He suggests that high market volatility may indicate oversold markets, hence signaling an attractive buy point. Subsequently, this generates positive future market returns. Thus, following his reasoning, it may seem that investors buy stocks performing well on the environmental factor when the market is oversold. We observe that the stock returns predicted by the abnormal VIX level only depends on the environmental score. Companies with higher environmental score generate higher returns the following day when investors are worried. The other scores are insignificant in predicting stock returns when VIX deviates from its one year median. Hence, there is little predictive power in ESG ratings in times of an abnormal high or low market uncertainty level.

Daily Changes in VIX Banerjee et al. (2007) find that both the VIX and the innovations in VIX are important for explaining stock returns. We therefore investigate how changes in market uncertainty from one day to another impact stock returns of sustainable firms. This captures more sudden changes in investor fear, as oppose to the more general level of concern that is captured by the VIX relative to its one year median. The results are presented in Table 15.

The daily change in VIX is in model (1) observed to be negatively related to stock returns. In other words, when market uncertainty increases, the stock returns fall. This is also found by French et al. (1987), Whaley (2000) and Sarwar (2012). As observed in model (2) and (5), the ESG and governance scores are significant and positive in explaining stock returns when market concern changes from the previous day. Model (2) reveals that the stock returns of companies with high ESG scores seem to be less sensitive to daily changes in market uncertainty. Moreover, models (3) - (5) revela that this result is driven by the governance score. As stipulated by Giese et al. (2021), the governance factor reflect short-term risks. Accordingly, one would expect the governance factor to be important when there is sudden changes in market uncertainty, as seen in model (5). The environmental and social score, reflecting long-term risks, seem to be less important when the market uncertainty changes from one day to another, compared to when the VIX is evaluated for one year back.

We next investigate whether the previous day's change in VIX can predict stock returns. The results are presented in Table 16. We observe in model (1) that a daily positive change in VIX is related to lower returns. We find that this relationship only depends on the social score, seen in model (4). A high social score contributes positively to the stock return one day after an increase in VIX. That is, when investor concern increases, companies with higher social scores experience higher returns one day later.

In this section, we presented evidence for superior returns of sustainable companies when investors are concerned. Our results indicate that the overall ESG and governance scores are the most important scores in explaining this. The environmental and social score tend to be more important in predictions.

3.4 Robustness

In the reported estimations we have not included standard risk measures, such as Fama-French factors. To check the validity of our results, we have also tested the presented relationships using abnormal returns, estimated as residuals of a Fama-French three-factor model, as dependent variable. This produces similar results, and the conclusions drawn from using return as dependent variable remain unchanged.[12] We conclude that our results are not due to our leaving out these factors.

4 Conclusion

Theoretical models lead us to investigate two types of relationships between stock returns and ESG (environmental, social and governance) concerns. The first effect (ESG level) concerns differences in long term (expected) returns as a function of ESG level. The second effect (ESG concerns) investigate (short term) price reactions during periods of ESG concerns, either at the company, or the economy, level.

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

We first analyze the ESG level effect, and establish that the stocks of companies with high ESG scores on average underperform.

Our second set of analyses looks at ESG concerns at the company level. We investigate how public attention to ESG topics and companies, measured by Google search volumes, affect stock returns. We find that high search volumes on ESG topics are related to higher stock returns for companies with high ESG, environmental and governance scores. Furthermore, in accordance with existing literature, increased attention to companies (measured by Google search volume) predicts negative returns the following week. However, we find that this relationship strongly depends on ESG scores. Increased attention to companies with positive ESG scores predicts positive returns, while increased attention to companies with negative scores predicts negative returns.

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

[12] These results are available upon request.

sentiment predicts higher returns the day after for these companies. Finally, we use the VIX to indicate the level of concern about the economy, and find that when the VIX is high, companies with high ESG scores generate higher returns than companies with low ESG scores.

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Table 1: Descriptive statistics for the Refinitiv ESG scores

The table describes ESG, Environmental(E), Social(S) and Governance(G) scores obtained from Refinitiv for the sample of US companies. Panel A: Descriptive statistics (Mean, median, minimum and maximum scores). Panel B: Correlation between scores.

Panel A: Descriptive statistics

	Measure			
Score	Mean	Median	Min	Max
ESG score	40.79	37.30	0.26	95.14
Environmental score	25.03	13.05	0.00	98.53
Social score	42.30	38.36	0.60	97.88
Governance score	50.05	50.62	0.04	98.72

Panel B: Correlations

Score	ESG score	Environmental score	Social score
Environmental score	0.859		
Social score	0.875	0.730	
Governance score	0.705	0.451	0.373

Table 2: Do different key words lead to different samples?

Correlation between abnormal Twitter volume, $AbTV$, based on each keyword.

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

Table 3: Example tweets with polarities.

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 via @ClimateHome #ESG	0	0	Negative	Neutral
Rise in index funds creates corporate governance risks #shareholderactivism https://t.co/51AhmxdTXQ	0	0	Negative	Neutral
You want to reduce the anxiety about #climatechange @ScottMorrisonMP - then fucking do something about it. #triggeredbygreta #auspol #climateemergency @GretaThunberg #ClimateCrisis #UnitedNations https://t.co/ZN5oluJ5O4	-0.6	-0.1027	Negative	Negative
Carrying a plastic bag in Kenya is now punishable with jail time https://t.co/rZRIuuOozK via @qzafrica #environment #sustainability	-0.1	-0.4404	Negative	Negative
Keep the environment and sustainability, because after all destroyed we will realize the money ill be eaten. #fz7	-0.5	-0.7184	Positive	Negative

Table 4: Matrices of tweet classification based on the sentiment analysis models.

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 5: Explaining stock returns with ESG

The table provides estimates of regressions explaining stock returns (R_{it} using company-level ESG, environmental (E), social (S) and governance (G) scores. The regressions include measures of daily trading volume ($AbVolume_{it}$), liquidity ($BidAsk_{it}$) and market capitalization ($MCAP_{it}$). Panel A shows results for an OLS regression. Panel B shows results for a regression including fixed company effects. Significance levels are indicated as $*p < 0.05, **p < 0.01$

Panel A: OLS regressions

	Endogenous variable: Daily return, R_{it}			
Exogenous variable	(1)	(2)	(3)	(4)
ESG_{it}	-0.1464**			
	(0.010)			
E_{it}		-0.0937**		
		(0.006)		
S_{it}			-0.0755**	
			(0.009)	
G_{it}				-0.0831**
				(0.008)
$AbVolume_{it}$	0.1125**	0.1122**	0.1125**	0.1133**
	(0.006)	(0.006)	(0.006)	(0.006)
$BidAsk_{it}$	-1.3241*	-1.2876*	-1.2841*	-1.3759*
	(0.552)	(0.552)	(0.553)	(0.553)
$MCAP_{it}$	0.0145**	0.0139**	0.0094**	0.0074**
	(0.002)	(0.002)	(0.003)	(0.002)
R^2	0.001	0.001	0.001	0.001
No. of observations	2 662 419	2 662 419	2 662 419	2 662 419

Panel B: Panel data regressions with company fixed effects

	Endogenous variable: Daily return, R_{it}			
Exogenous variable	(1)	(2)	(3)	(4)
ESG_{it}	-0.0033**			
	(0.000)			
E_{it}		-0.0025**		
		(0.000)		
S_{it}			-0.0024**	
			(0.000)	
G_{it}				-0.0011**
				(0.000)
$AbVolume_{it}$	0.1134**	0.1136**	0.1136**	0.1140**
	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.6591*	-1.6638*	-1.6690*	-1.6948*
	(0.685)	(0.685)	(0.685)	(0.684)
$MCAP_{it}$	0.1636**	0.1609**	0.1603**	0.1516**
	(0.008)	(0.008)	(0.008)	(0.007)
R^2	0.001	0.001	0.001	0.001
No. of observations	2 662 419	2 662 419	2 662 419	2 662 419

Table 6: Explaining Stock Returns with ESG and Google Search Volume

Panel data regressions with company fixed effects explaining stock returns of companies with different ESG, environmental (E), social (S) and governance (G) scores using Search Volume Index, SVI, on company names. Significance level indicated as $*p < 0.05$, $**p < 0.01$.

	Endogenous variable: Weekly return, R_{it}				
Exogenous variable	(1)	(2)	(3)	(4)	(5)
$AbSVI_t$	-0.0619* (0.026)	-0.1225 (0.063)	-0.0760* (0.035)	-0.0374 (0.028)	-0.2159 (0.116)
$AbSVI_t \times \text{ESG}_{it}$		0.1701 (0.111)			
$AbSVI_t \times \text{E}_{it}$			0.0771 (0.063)		
$AbSVI_t \times \text{S}_{it}$				-0.0657 (0.080)	
$AbSVI_t \times \text{G}_{it}$					0.3301 (0.197)
$AbVolume_{it}$	-0.6126* (0.251)	-0.6132* (0.251)	-0.6129* (0.251)	-0.6125* (0.251)	-0.6142* (0.252)
$BidAsk_{it}$	48.952** (13.612)	48.952** (13.612)	48.950** (13.612)	48.951** (13.612)	48.949** (13.612)
$MCAP_{it}$	0.7721** (0.219)	0.7724** (0.219)	0.7720** (0.219)	0.7720** (0.219)	0.7734** (0.218)
R^2	0.002	0.002	0.002	0.002	0.002
No. of observations	581 655	581 655	581 655	581 655	581 655

Table 7: Predicting stock returns with ESG and SVI

Panel data regressions with company fixed effects predicting stock returns of companies with different ESG, environmental (E), social (S) and governance (G) scores using the Search Volume Index, SVI, on company names. Significance level indicated as $*p < 0.05, **\,p < 0.01$

	Endogenous variable: Weekly return, R_{it}				
Exogenous variable	(1)	(2)	(3)	(4)	(5)
$AbSVI_{t-1}$	-0.0733**	-0.1817**	-0.1047**	-0.1398**	-0.1596**
	(0.015)	(0.051)	(0.023)	(0.043)	(0.053)
$AbSVI_{t-1} \times ESG_{i,t-1}$		0.3042**			
		(0.110)			
$AbSVI_{t-1} \times E_{i,t-1}$			0.1720**		
			(0.054)		
$AbSVI_{t-1} \times S_{i,t-1}$				0.1785*	
				(0.083)	
$AbSVI_{t-1} \times G_{it-1}$					0.1851*
					(0.092)
$AbVolume_{i,t-1}$	-0.4188*	-0.4198*	-0.4195*	-0.4190*	-0.4197*
	(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)
$MCAP_{i,t-1}$	-1.0670**	-1.0665**	-1.0672**	-1.0668**	-1.0663**
	(0.119)	(0.119)	(0.119)	(0.119)	(0.118)
R^2	0.003	0.003	0.003	0.003	0.003
No. of observations	581 600	581 600	581 600	581 600	581 600

Table 8: Explaining stock returns with ESG and SVI (by ESG topic)

Panel data regressions with company fixed effects explaining stock returns of companies with different ESG, environmental (E), social (S) and governance (G) score using Search Volume Indices, SVIs, on ESG, social, environmental and governance topics. Significance level indicated as $*p < 0.05, **p < 0.01$

	Endogenous variable: Daily return, R_{it}							
Exogenous variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AbSVI_{ESG,t}$	-0.0172** (0.005)	-0.0697** (0.013)						
$AbSVI_{ESG,t} \times \mathrm{ESG}_t$		0.1298** (0.024)						
$AbSVI_{E,t}$			-0.0156** (0.003)	-0.0261** (0.005)				
$AbSVI_{E,t} \times \mathrm{E}_t$				0.0433** (0.010)				
$AbSVI_{S,t}$					-0.0161** (0.005)	-0.0274** (0.010)		
$AbSVI_{S,t} \times \mathrm{S}_t$						0.0269 (0.019)		
$AbSVI_{G,t}$							0.0454** (0.005)	-0.0225 (0.015)
$AbSVI_{G,t} \times \mathrm{G}_t$								0.1358** (0.025)
$AbVolume_{it}$	0.1153** (0.007)	0.1149** (0.007)	0.1153** (0.007)	0.1151** (0.007)	0.1153** (0.007)	0.1152** (0.007)	0.1118** (0.007)	0.1116** (0.007)
$BidAsk_{it}$	-1.7050* (0.684)	-1.6965* (0.685)	-1.7015* (0.685)	-1.6958* (0.685)	-1.7031* (0.685)	-1.7015* (0.685)	-1.6989* (0.684)	-1.6958* (0.684)
$MCAP_{it}$	0.1475** (0.007)	0.1480** (0.007)	0.1477** (0.007)	0.1478** (0.007)	0.1473** (0.007)	0.1474** (0.007)	0.1475** (0.007)	0.1475** (0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
No. of observations	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: Predicting stock returns with ESG and SVI

Panel data regressions with company fixed effects predicting stock returns of companies with different ESG, environmental (E), social (S) and governance (G) score using Search Volume Indices, SVIs, for ESG, environmental, social and governance topics. Significance level indicated as $*p < 0.05$, $**\ p < 0.01$

	Endogenous variable: Daily return, R_{it}							
Exogenous variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AbSVI_{ESG,\ t-1}$	0.0296**	0.0326*						
	(0.005)	(0.013)						
$AbSVI_{ESG,\ t-1} \times \text{ESG}_{i,t-1}$		-0.0074						
		(0.025)						
$AbSVI_{E,\ t-1}$			0.0311**	0.0286**				
			(0.003)	(0.005)				
$AbSVI_{E,\ t-1} \times \text{E}_{i,t-1}$				0.0104				
				(0.011)				
$AbSVI_{S,\ t-1}$					0.0431**	0.0450**		
					(0.004)	(0.010)		
$AbSVI_{S,\ t-1} \times \text{S}_{i,t-1}$						-0.0045		
						(0.020)		
$AbSVI_{G,\ t-1}$							0.0820**	0.0950**
							(0.005)	(0.016)
$AbSVI_{G,\ t-1} \times \text{G}_{i,t-1}$								-0.0260
								(0.026)
$AbVolume_{i,t-1}$	0.0321**	0.0321**	0.0318**	0.0318**	0.0313**	0.0313**	0.0302**	0.0302**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$BidAsk_{i,t-1}$	0.3443	0.3439	0.3368	0.3379	0.3391	0.3389	0.3514	0.3510
	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)
$MCAP_{i,t-1}$	-0.1908**	-0.1908**	-0.1913**	-0.1913**	-0.1904**	-0.1905**	-0.1909**	-0.1909**
	(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. of observations	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 10: explaining stock returns using ESG and abnormal Twitter volume

Panel data regressions with company fixed effects explaining stock returns of companies with different ESG, environmental (E), social (S) and governance (G) score using abnormal Twitter volume, AbTV, for the five keywords. Significance level indicated as $*p < 0.05, **\, p < 0.01$

	Endogenous variable: Daily return, R_{it} Keyword:													
	ESG		Sustainability		Climate change			Social responsibility				Corporate governance		
Exogenous Variable	(1)	(2)	(1)	(2)	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(1)	(2)	(3)
$AbTV_t$	-0.0061	-0.0248*	-0.0298**	-0.0407**	-0.0272**	-0.0146	-0.0214**	0.0350**	0.0520**	0.0228**	0.0825**	-0.0362**	-0.0322**	-0.0485**
	(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)
$AbTV_t \times ESG_{it}$		0.0450		0.0267**		-0.0313			-0.0420*				0.0098	
		(0.024)		(0.027)		(0.018)			(0.019)				(0.021)	
$AbTV_t \times E_{it}$							-0.0239*							
							(0.012)							
$AbTV_t \times S_{it}$										0.0291				
										(0.016)				
$AbTV_t \times G_{it}$											-0.0952**			0.0245
											(0.018)			(0.019)
$Volume_{it}$	0.1144**	0.1144**	0.1151**	0.1151**	0.1148**	0.1149**	0.1149**	0.1129**	0.1129**	0.1129**	0.1129**	0.1152**	0.1152**	0.1151**
	(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)
$BidAsk_{it}$	-1.7047*	-1.7059*	-1.7063*	-1.7065*	-1.7095*	-1.7093*	-1.7098*	-1.6911*	-1.6550*	-1.6915*	-1.6906*	-1.7115*	-1.7114*	-1.7113*
	(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)
$MCAP_{it}$	0.1471**	0.1469**	0.1463**	0.1469**	0.1488**	0.1489**	0.1488**	0.1489**	0.1490**	0.1489**	0.1491**	0.1455**	0.1455**	0.1455**
	(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. of observations	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 11: Explaining stock returns with ESG and Twitter, including MOOD

Panel data regressions with company fixed effects explaining stock returns of companies with different ESG, environmental (E), social (S) and governance (G) scores using the abnormal positive Twitter volume, $AbTV^+$, abnormal negative Twitter volume, $AbTV^-$, and the MOOD. The MOOD is the overall Twitter sentiment. Significance level indicated as $*p < 0.05, **p < 0.01$

Panel A: Keyword: ESG

	Endogenous variable: Daily return, R_{it}					
Exogenous variable	(1)	(2)	(3)	(4)	(5)	(6)
$MOOD_t$	-0.3877** (0.019)	-0.1994** (0.033)				
$MOOD_t \times ESG_{it}$		-0.3856** (0.053)				
$AbTV_t^+$			-0.0329** (0.004)	-0.0458** (0.011)		
$AbTV_t^+ \times ESG_{it}$				0.0310 (0.021)		
$AbTV_t^-$					-0.0397** (0.004)	-0.0497** (0.004)
$AbTV_t^- \times ESG_{it}$						0.0644** (0.007)
$AbVolume_{it}$	0.1148** (0.007)	0.1145** (0.007)	0.1156** (0.007)	0.1156** (0.007)	0.1154** (0.007)	0.1144** (0.007)
$BidAsk_{it}$	-1.6214* (0.686)	-1.6063* (0.686)	-1.7095* (0.684)	-1.7104* (0.684)	-1.7027* (0.684)	-1.6907* (0.684)
$MCAP_{it}$	0.1672** (0.008)	0.1721** (0.008)	0.1459** (0.007)	0.1457** (0.007)	0.1459** (0.007)	0.1469** (0.007)
R^2	0.001	0.001	0.001	0.001	0.001	0.001
No. of observations	2 662 419	2 662 419	2 662 419	2 662 419	2 662 419	2 662 419

Table 11: (Continued)

Panel B: Keyword: Sustainability

	Endogenous variable: Daily return, R_{it}					
Exogenous variable	(1)	(2)	(3)	(4)	(5)	(6)
$MOOD_t$	-0.6204**	-0.4945**				
	(0.028)	(0.037)				
$MOOD_t \times ESG_{it}$		-0.2023**				
		(0.039)				
$AbTV_t^+$			-0.0224**	-0.0306*		
			(0.005)	(0.013)		
$AbTV_t^+ \times ESG_{it}$				0.0200		
				(0.025)		
$AbTV_t^-$					-0.0711**	-0.0702**
					(0.005)	(0.013)
$AbTV_t^- \times ESG_{it}$						-0.0020
						(0.024)
$AbVolume_{it}$	0.1119**	0.1118**	0.1149**	0.1149**	0.1162**	0.1162**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.5536*	-1.5474*	-1.7053*	-1.7056*	-1.6971*	-1.6970*
	(0.687)	(0.687)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.1818**	0.1847**	0.1470**	0.1470**	0.1469**	0.1469**
	(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. of observations	2 662 419	2 662 419	2 662 419	2 662 419	2 662 419	2 662 419

Table 11: (Continued)

Panel C: Keyword: Climate change

	Endogenous variable: Return								
Exogenous variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MOOD_t$	-0.4572**	-0.4232**	-0.4566**						
	(0.021)	(0.051)	(0.030)						
$MOOD_t \times ESG_{it}$		-0.0829							
		(0.099)							
$MOOD_t \times E_{it}$			-0.0023						
			(0.064)						
$AbTV_t^+$				-0.0473**	-0.0413**	-0.0436**			
				(0.004)	(0.010)	(0.006)			
$AbTV_t^+ \times ESG_{it}$					-0.0150				
					(0.019)				
$AbTV_t^+ \times E_{it}$						-0.0153			
						(0.012)			
$AbTV_t^-$							-0.0119**	-0.0141**	-0.0141**
							(0.003)	(0.003)	(0.003)
$AbTV_t^- \times ESG_{it}$								0.0465**	
								(0.006)	
$AbTV_t^- \times E_{it}$									0.0465**
									(0.006)
$AbVolume_{it}$	0.1156**	0.1156**	0.1156**	0.1155**	0.1156**	0.1156**	0.1144**	0.1135**	0.1135**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.6544*	-1.6540*	-1.6544**	-1.7083*	-1.7083*	-1.7085**	-1.7033**	-1.6947**	-1.6647**
	(0.685)	(0.685)	(0.685)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.1486**	0.1488**	0.1486**	0.1497**	0.1498**	0.1498**	0.1482**	0.1492**	0.1492**
	(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. of observations	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 11: (Continued)

Panel D: Keyword: Social responsibility

	Endogenous variable: Daily return, R_{it}											
Exogenous variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$MOOD_t$	-0.0682**	0.1027**	0.0612**	0.0083								
	(0.016)	(0.020)	(0.019)	(0.019)								
$MOOD_t \times ESG_{it}$		-0.4282**										
		(0.030)										
$MOOD_t \times S_{it}$			-0.3132**									
			(0.026)									
$MOOD_t \times G_{it}$				-0.1550**								
				(0.018)								
$AbTV_t^+$					0.0373**	0.0520**	0.0254**	0.0801**				
					(0.004)	(0.009)	(0.008)	(0.010)				
$AbTV_t^+ \times ESG_{it}$						-0.0363*						
						(0.018)						
$AbTV_t^+ \times S_{it}$							0.0282					
							(0.015)					
$AbTV_t^+ \times G_{it}$								-0.0858**				
								(0.017)				
$AbTV_t^-$									0.0407**	0.0663**	0.0604**	0.0614**
									(0.003)	(0.008)	(0.008)	(0.009)
$AbTV_t^- \times ESG_{it}$										-0.0617**		
										(0.017)		
$AbTV_t^- \times S_{it}$											-0.0460**	
											(0.015)	
$AbTV_t^- \times G_{it}$												-0.0410**
												(0.016)
$AbVolume_{it}$	0.1144**	0.1137**	0.1139**	0.1142**	0.1127**	0.1127**	0.1127**	0.1127**	0.1131**	0.1131**	0.1131**	0.1130**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.7111*	-1.6744*	-1.6823*	-1.7025*	-1.6877*	-1.6873*	-1.6881*	-1.6871*	-1.7021*	-1.7005*	-1.7011*	-1.7014**
	(0.685)	(0.685)	(0.685)	(0.685)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.1471**	0.1610**	0.1581**	0.1510**	0.1491**	0.1491**	0.1491**	0.1492**	0.1477**	0.1478**	0.1478**	0.1478**
	(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. of observations	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 11: (Continued)

Panel E: Keyword: Corporate governance

	Endogenous variable: Daily return, R_{it}								
Exogenous variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MOOD_t$	-0.0384**	0.0784**	0.0350						
	(0.011)	(0.024)	(0.022)						
$MOOD_t \times ESG_{it}$		-0.2803**							
		(0.047)							
$MOOD_t \times G_{it}$			-0.1448**						
			(0.034)						
$AbTV_t^+$				-0.0415**	-0.0546**	-0.0620**			
				(0.004)	(0.009)	(0.010)			
$AbTV_t^+ \times ESG_{it}$					0.0319				
					(0.018)				
$AbTV_t^+ \times G_{it}$						0.0410*			
						(0.017)			
$AbTV_t^-$							-0.0284**	-0.0061	-0.0253**
							(0.003)	(0.006)	(0.007)
$AbTV_t^- \times ESG_{it}$								-0.0538**	
								(0.013)	
$AbTV_t^- \times G_{it}$									-0.0063
									(0.012)
$AbVolume_{it}$	0.1141**	0.1139**	0.1140**	0.1153**	0.1153**	0.1153**	0.1152**	0.1152**	0.1152**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$BidAsk_{it}$	-1.6990*	-1.6870*	-1.6956*	-1.7037*	-1.7042*	-1.7039*	-1.7098*	-1.7089*	-1.7098*
	(0.685)	(0.685)	(0.685)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)	(0.684)
$MCAP_{it}$	0.1479**	0.1516**	0.1494**	0.1458**	0.1457**	0.1457*	0.1469**	0.1472**	0.1469**
	(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. of observations	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 12: Predicting stock returns with ESG and Twitter mood

Panel data regressions with company fixed effects predicting stock returns of companies with different ESG, environmental (E), social (S) and governance (G) scores using Twitter mood for the selected keywords. Significance level indicated as $*p < 0.05, **p < 0.01$.

	Endogenous variable: Daily return, R_{it}													
	Keyword:													
	ESG		Sustainability		Climate change			Social responsibility				Corporate governance		
Exogenous Variable	(1)	(2)	(1)	(2)	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(1)	(2)	(3)
$MOOD_{t-1}$	0.0744**	-0.2024**	0.2499**	-0.0082	-0.4220**	-0.7153**	-0.5170**	-0.1767**	-0.3201**	-0.3252**	-0.2185**	-0.0250*	-0.2323**	-0.1068**
	(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)
$MOOD_{t-1} \times ESG_{i,t-1}$		0.5649**		0.4151**		0.7155**			0.3602**				0.4964**	
		(0.055)		(0.041)		(0.107)			(0.031)				(0.047)	
$MOOD_{t-1} \times E_{i,t-1}$							0.3713**							
							(0.073)							
$MOOD_{t-1} \times S_{i,t-1}$										0.3605**				
										(0.027)				
$MOOD_{t-1} \times G_{i,t-1}$											0.0849**			0.1611**
											(0.019)			(0.035)
$AbVolume_{i,t-1}$	0.0335**	0.0338**	0.0345**	0.0346**	0.0344**	0.0343**	0.0343**	0.0338**	0.0345**	0.0344**	0.0340**	0.0333**	0.0337**	0.0334**
	(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)
$BidAsk_{i,t-1}$	0.3280**	0.3073**	0.2825**	0.2711**	0.3931**	0.3887**	0.3908**	0.3310**	0.3007**	0.2986	0.3263**	0.2516**	0.3327**	0.3327**
	(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)
$MCAP_{i,t-1}$	-0.1946**	-0.2018**	-0.2046**	-0.2106**	-0.1899**	-0.1918**	-0.1908**	-0.1918**	-0.2034**	-0.2045**	-0.1939**	-0.1905**	-0.1972**	-0.1922**
	(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. of observations	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 13: Explaining stock returns with ESG and VIX

Panel data regressions with company fixed effects explaining stock returns of companies with different ESG, environmental (E), social (S) and governance (G) score using the deviation in VIX from its one year rolling median, AbVIX. Significance level indicated as $*p < 0.05, **p < 0.01$

	Endogenous variable: Daily return, R_{it}				
Exogenous variable	(1)	(2)	(3)	(4)	(5)
$AbVIX_t$	-0.8926** (0.006)	-0.9636** (0.014)	-0.9219** (0.008)	-0.9046** (0.013)	-0.9911** (0.015)
$AbVIX_t \times ESG_{it}$		0.1735** (0.031)			
$AbVIX_t \times E_{it}$			0.1164** (0.021)		
$AbVIX_t \times S_{it}$				0.0283** (0.028)	
$AbVIX_t \times G_{it}$					0.1962** (0.068)
$AbVolume_{it}$	0.1373** (0.003)	0.1368** (0.003)	0.1368** (0.003)	0.1372** (0.003)	0.1368** (0.003)
$BidAsk_{it}$	0.8813** (0.094)	0.8893** (0.094)	0.8875** (0.094)	0.8820** (0.094)	0.8920** (0.094)
$MCAP_{it}$	0.1800** (0.004)	0.1798** (0.004)	0.1800** (0.004)	0.1799** (0.004)	0.1801** (0.004)
R^2	0.010	0.010	0.010	0.010	0.010
No. of observations	2 662 419	2 662 419	2 662 419	2 662 419	2 662 419

Table 14: Predicting stock returns with ESG and VIX

Panel data regressions with company fixed effects predicting stock returns of companies with different ESG, environmental (E), social (S) and governance (G) score using the deviation in VIX from its one year rolling median, AbVIX. Significance levels indicated as $*p < 0.05, **\ p < 0.01$.

	Endogenous variable: Daily return, R_{it}				
	(1)	(2)	(3)	(4)	(5)
Exogenous variable					
$AbVIX_{t-1}$	0.1410** (0.006)	0.1245** (0.052)	0.1244** (0.008)	0.1291** (0.014)	0.1358** (0.015)
$AbVIX_{t-1} \times ESG_{i,t-1}$		0.0403 (0.032)			
$AbVIX_{t-1} \times E_{i,t-1}$			0.0659** (0.075)		
$AbVIX_{t-1} \times S_{i,t-1}$				0.0280 (0.092)	
$AbVIX_{t-1} \times G_{i,t-1}$					0.0103 (0.028)
$AbVolume_{i,t-1}$	0.0297** (0.003)	0.0296** (0.003)	0.0294** (0.003)	0.0296** (0.003)	0.0296** (0.003)
$BidAsk_{i,t-1}$	-0.0566 (0.096)	-0.0548 (0.096)	-0.0532 (0.096)	-0.0560 (0.096)	-0.0560 (0.096)
$MCAP_{i,t-1}$	-0.1960** (0.004)	-0.1960** (0.004)	-0.1959** (0.004)	-0.1960** (0.004)	-0.1959** (0.004)
R^2	0.001	0.001	0.001	0.001	0.001
No. of observations	2 564 305	2 564 305	2 564 305	2 564 305	2 564 305

Table 15: Explaining Stock Returns with ESG and lagged VIX deviations

Panel data regressions with company fixed effects explaining stock returns of companies with different ESG, environmental (E), social (S) and governance (G) score using deviations in VIX from the previous day's VIX, ΔVIX. Significance level indicated as $*p < 0.05, **p < 0.01$.

	Endogenous variable: Daily return, R_{it}				
Exogenous variable	(1)	(2)	(3)	(4)	(5)
ΔVIX_t	-9.0875** (0.016)	-9.4631** (0.038)	-9.1133** (0.022)	-9.0827** (0.037)	-9.7827** (0.041)
$\Delta VIX_t \times ESG_{it}$		0.9286** (0.086)			
$\Delta VIX_t \times E_{it}$			0.1059 (0.058)		
$\Delta VIX_t \times S_{it}$				-0.0114 (0.078)	
$\Delta VIX_t \times G_{it}$					1.3929** (0.075)
$AbVolume_{it}$	0.1271** (0.003)	0.1269** (0.003)	0.1270** (0.003)	0.1271** (0.003)	0.1269** (0.003)
$BidAsk_{it}$	0.7674** (0.088)	0.7645** (0.088)	0.7668** (0.088)	0.7674** (0.088)	0.7669** (0.088)
$MCAP_{it}$	0.1632** (0.004)	0.1630** (0.004)	0.1631** (0.004)	0.1632** (0.004)	0.1630** (0.004)
R^2	0.106	0.106	0.106	0.106	0.107
No. of observations	2 662 419	2 662 419	2 662 419	2 662 419	2 662 419

Table 16: Explaining Stock Returns with ESG and lagged VIX surprises

Panel data regressions with company fixed effects predicting stock returns of companies with different ESG, environmental (E), social (S) and governance (G) score using deviations in VIX from the previous day's VIX, ΔVIX. Significance level indicated as $*p < 0.05, **\, p < 0.01$

	Endogenous variable: Daily return, R_{it}				
Exogenous variable	(1)	(2)	(3)	(4)	(5)
ΔVIX_{t-1}	-0.0493** (0.017)	-0.1129** (0.041)	-0.0616** (0.023)	-0.1838** (0.039)	-0.0114 (0.044)
$\Delta VIX_{t-1} \times ESG_{i,t-1}$		0.1572 (0.089)			
$\Delta VIX_{t-1} \times E_{i,t-1}$			0.0505 (0.063)		
$\Delta VIX_{t-1} \times S_{i,t-1}$				0.3204** (0.084)	
$\Delta VIX_{t-1} \times G_{i,t-1}$					-0.0758 (0.080)
$Volume_{i,t-1}$	0.0335** (0.003)	0.0335** (0.003)	0.0335** (0.003)	0.0335** (0.003)	0.0335** (0.003)
$BidAsk_{i,t-1}$	0.3572** (0.095)	0.3566* (0.095)	0.3568** (0.095)	0.3557** (0.095)	0.3572** (0.090)
$MCAP_{i,t-1}$	-0.1907** (0.004)	-0.1908** (0.004)	-0.1907** (0.004)	-0.1908** (0.004)	-0.1907** (0.004)
R^2	0.001	0.001	0.001	0.001	0.001
No. of observations	2 564 305	2 564 305	2 564 305	2 564 305	2 564 305