

ESG investing and media attention to environmental issues

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Abstract

The study of investments that ensure environmentally responsible and sustainable development is becoming an increasingly relevant research topic in the field of empirical asset pricing. In this paper, we analyse how ESG scores' effect on future returns change when environmental issues receive relatively high media coverage. Investors might only take environmental issues into account if they are confronted with the problem of global warming more frequently in the press. We assess the importance of environmental issues in media with machine learning based Structural Topic Modelling (STM) methodology using news published in US. Running Fama-MacBeth regressions we find that in periods, when media actively reports on environmental issues ESG scores have significant impact on future returns. Whereas, in months when fewer such articles are published investors do not take sustainability measures into account, and ESG scores have no explanatory power.

Keywords: ESG; environmental issues, investors' attention, Structural Topic Model, Fama-MacBeth regression

1. Introduction

The study of investments that ensure environmentally responsible and sustainable development is becoming an increasingly relevant research topic in the field of empirical asset pricing. Corporate management has also recognised the importance of environmental awareness and sustainability (Flammer 2013). ESG score is a commonly used indicator to measure a firms' commitment to tackle environmental and social issues (Townsend 2020). ESG consists of three pillars: environmental, social and governance score. The scores measure compliance with the given criteria, thus it can be used as a measure of sustainability. Following Auer and Schuhmacher (Auer and Schuhmacher 2016) this study also uses ESG pillar scores to assess the firm's attitude towards environmental issues. There are many different similar measures, however, Talan and Sharma present (Talan and Sharma 2019) that ESG is one of the most effective and widely used indicator.

Being environmentally and socially responsible might be beneficial for a company, as it might be seen as a competitive advantage in the capital market. Previous research provides evidence of lower cost of capital for companies with higher ESG score. (Kotsantonis and Serafeim 2019) Sustainable operations might also lead to higher efficiency (Gillan et al. 2010) and affect the return on equity or return on assets. (Buallay 2018) For this reason, investors might prefer firms with sustainable

To support reproducibility and understanding, the R codes used in this study are available in the following Github repository: <https://github.com/MarcellGranat/green-finance>

management, which is reflected in stock prices and future returns. However, previous research present contradicting results. In their study, Sahut and Pasquini-Descomps (Sahut and Pasquini-Descomps 2015) analyse ESG and stock returns in US, UK and Swiss markets over the period 2007–2011 and find ESG to be significant only for United Kingdom. While other sector-specific research (Buallay 2018) find that ESG among US banks had a significant impact on returns between 2007 and 2016. Results suggest that there might be regional differences in investors' preferences for ESG investing. There is no significant impact at an industry level on US and Asia-Pacific regions, however, in Europe investors might be paying a premium for green stocks. Using different approaches (e.g., Jain, Sharma, and Srivastava 2019 Naffa and Fain 2020; Naffa and Fain 2022) usually yield mixed results on ESG and expected returns. (Auer and Schuhmacher 2016).

Inconclusive results have led to a number of studies on what drives investors' perceptions about the importance of environmental issues. Due to people's limited attention (e.g., Hirshleifer and Teoh 2003; Neszveda 2018), they are more likely to pay attention to environmental issues if they are confronted with it more frequently or if they experience extreme weather events. Studies (Li, Johnson, and Zaval 2011), (Akerlof et al. 2013) report that personal experiences matter a lot. They find that recent experience with global warming (such as extreme weather or natural disasters) increases the perception of climate risk in the United States. Choi (Choi, Gao, and Jiang 2020) finds that retail investors sell carbon-intensive firms in case of abnormal weather experienced in their surroundings. The impact of extreme weather is strengthened by the more intensive media coverage of environmental issues in these periods. Schmidt show (Schmidt 2015) that media attention to climate change increases in the record-breaking warmest years than in "normal" years. This suggest that in periods of intensive media coverage, investors pay more attention to climate change, relative to periods when these issues receive limited media coverage.

In this paper, we analyse how ESG scores' affect on future returns change when environmental issues receive relatively high media coverage. People might be more likely to pay attention to those information, which they see more frequently. Research showed (e.g. DellaVigna and Pollet 2009 or Hirshleifer and Teoh 2003) that investors' attention is also limited. For this reason they might only take environmental issues into account if they are confronted with the problem of global warming more frequently. Seeing more articles in the topic they change their perceptions about the importance of sustainability and choose their investments accordingly. If this mechanism exists than its impact can be showed through the changes in stock prices.

Based on this our hypothesis is that in periods, when media actively reports on environmental issues ESG scores have significant impact on future returns. Whereas, in months when fewer such articles are published investors do not take sustainability measures into account, therefore ESG scores have no explanatory power.

We assess the importance of environmental issues in media with machine learning based Structural Topic Modelling (STM) methodology. For this purpose, we use a publicly available news archive, which is a collection of news published on investing.com. The model found an environmental topic and calculated its relative importance (*gamma*) in the article. By averaging article level *gamma* values in a given month, we get the importance of environmental related topics for that month.

In our analysis, we run Fama-MacBeth (Fama and MacBeth 1973) regressions using observations in months when environmental issues received higher than average (lower than average) media coverage based on their respective *gamma*. These months will be referred to as intensive (non-intensive) periods.

Despite ESG coefficients being statistically significant in regression, the average future return is much lower on ESG scores compared to the factors of Fama-French's four factor model (Carhart 1997). This shows that investors do not value sustainability to such extent that its impact can be considered economically significant. (Ashwin Kumar et al. 2016)

However, we find that in periods of intensive environmental media coverage *Social Score* and

Governance Score significantly affect future returns, while in low-intensity periods they have no explanatory power. These findings are robust to different definitions of intensive and non intensive periods. Moreover, we find that using median as a threshold to define high media-intensity periods all of the ESG pillar scores significantly predict future returns.

These result implies that investors pay attention to ESG scores when environmental issues receive high media coverage. But in months when investors are less confronted with environmental problems in the press they take these issues into account in their investments to a lesser extent.

Section 2 describes the data used in the analysis, data cleaning and provides summary statistics. *Section 3* details the Structural Topic Modelling and Fama-MacBeth regression methodologies. *Section 4* present our results, while *Section 5* summarises our conclusions along with its limitations.

2. Data

In this section we present in detail the databases used in the analysis. First we describe stock news data, then data on company information and stocks' performance. In the last subsection we provide descriptive statistics on our data.

2.1 Stock news data

In addition to the financial data, we need a text (unstructured) data in which it is possible to quantify the intensity of the green topic at a given moment. For this purpose, we use a publicly available news archive, which is a collection of news published on investing.com. The data is available at: <https://www.kaggle.com/datasets/gennadiyr/us-equities-news-data>

The dataset contains news from 2008, however it is complete without interruption only from 2010 and ends in 2020. The news are related to US equities, which are publicly traded on NYSE/NASDAQ and in 2020 still has a price higher than 10\$ per share.

During the analysis we use the daily frequency in the topic modeling to form the prevalence of topics (see chapter 3.1), but then we will aggregate the intensity of the green topic in the articles to a monthly level.

2.2 Stock and company data

We use monthly data on stocks traded on the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ) stock exchanges. Due to accessibility, the Refinitiv Datastream (former Thomson Reuters Datastream, TDS) was used instead of the most common Center for Research in Security Prices database (CRSP). Ince and Porter (2006) reports that after cleaning, the inferences drawn from TDS data are similar to those drawn from CRSP.

Our data consist of active and inactive primary equities. To avoid delisting bias (or survival bias) inactive stocks are also included. (Shumway 1997) The one-month US treasury bills are used as risk-free return.¹

The following variables were obtained through TDS :

- **Unadjusted Price:** price quoted at the first day of the respective month, data in \$ (Datastream database)
- **Total Return Index:** following the literature we use total return index as a performance measure, as it adjusts for price movements due to split and dividend payments (Datastream database)
- **Turnover by Volume:** number of stocks traded on the respective month, data in thousands (Datastream database)
- **Common Shares Outstanding:** the number of common shares outstanding at the end of the year (Worldscope database)

1. Downloaded from Stambaugh's website (<https://finance.wharton.upenn.edu/stambaugh/>) on 10th March 2022

- **Book Value per Share:** book value per share at the end of the respective fiscal year, data in \$ (Worldscope database)
- **Environment Pillar Score:** Refinitiv's Environment Pillar Score is the weighted average relative rating of a company based on the reported environmental information and the resulting three environmental category scores.
- **Social Pillar Score:** Refinitiv's Social Pillar Score is the weighted average relative rating of a company based on the reported social information and the resulting four social category scores.
- **Governance Pillar Score:** Refinitiv's Governance Pillar Score is the weighted average relative rating of a company based on the reported governance information and the resulting three governance category scores.

Using these variables the following indicators have been created:

- **Market beta:** systematic risk. Beta was estimated running the following OLS regression model on our data. (Using a 36 month rolling window, requiring at least 30 observation per month.)

$$r_{i,t} - r_{f,t} = \alpha + \beta_{i,t} \cdot (r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad (1)$$

Where $r_{i,t}$ is the return on asset i in period t ; $r_{f,t}$ is the risk-free return in period t ; $r_{m,t}$ is the market return in period t ; α is the intercept of the model; $\beta_{i,t}$ is the market beta of asset i in period t ; and $\varepsilon_{i,t}$ is the error term in period t .

- **Market value:** the market capitalization of the stock i in month t

$$size_{i,t} = \ln(\text{common shares outstanding}_{i,t} \cdot \text{unadjusted price}_{i,t}) \quad (2)$$

Where *common shares outstanding* _{i,t} is the number of firms i 's common shares outstanding at the end of the year to which month t belongs, *unadjusted price* _{i,t} is i 's \$ price quoted at the first day of month t .

- **Book-to-market-ratio:** stock i 's B/M in month t .

$$btm_{i,t} = \ln\left(\frac{\text{book value per share}_{i,t}}{\text{unadjusted price}_{i,t}}\right) \quad (3)$$

Where *book value per share* _{i,t} is firm i 's \$ book value per share at the end of the fiscal year to which month t belongs, and *unadjusted price* _{i,t} is i 's \$ price quoted at the first day of month t .

- **Momentum:** the average return on asset i over the last 3 to twelve months. (Carhart 1997)

When cleaning the data we follow the procedures proposed by Ince – Porter (Ince and Porter 2006) with a few modifications and additions. They suggest deleting stocks traded at prices below 5 \$. However, our news database represents a news archive of US equities publicly traded on NYSE/NASDAQ, which still has a price higher than 10 \$ per share. For this reason we used 10 \$ as a threshold instead of 5 \$. As seen in Figure 1 firms with prices below 10 \$ generally have smaller market capitalization. Before dropping stocks with price lower than 10 \$ the 5th percentile of size was 12.46. After excluding stocks with price lower than 10 \$, only 1% of the firms have a size below 12.14. For this reason we did not delete the smallest stocks: dropping stocks with low prices partially tackles the problem of small firms. Otherwise, dropping the smallest 5% of firms is a common way of screening for small firms.

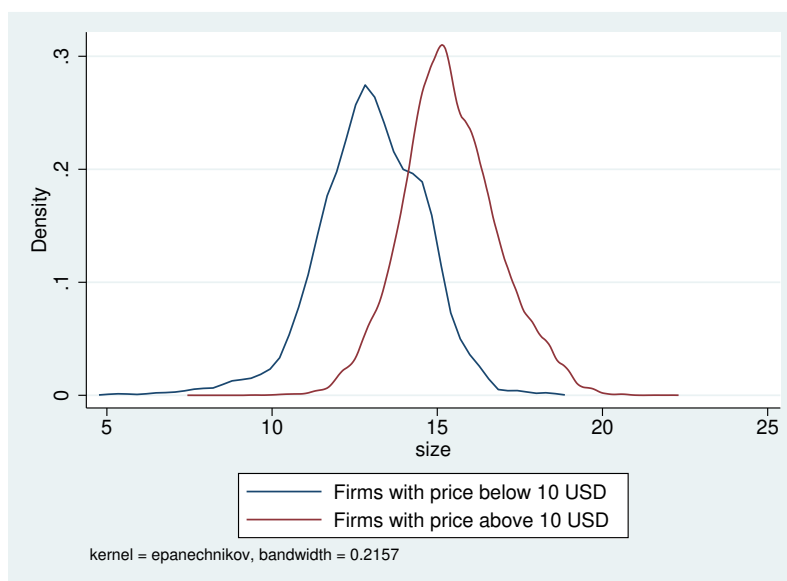


Figure 1. Kernel Density of firms below and above 10 \$

We also delete the most illiquid stocks in every month. (1st decile based on turnover) (Amihud 2002) Observations with return equal to zero or over 200% were excluded. Observations with total return index smaller than 0.01 were also omitted. Lastly, we dropped observations with missing variables, and excluded months which had less than 50 observations after data cleansing.

Our news data includes articles from October 2008 to February 2020. However, due to the limited number of documents at the beginning of the time period, STM did not find any document related to environmental topic in November and December of 2009. For this reason, we analyse returns from January 2010 to February 2020.

After cleaning, our database contains 97 178 observations for 1 983 firms, covering the 122 months between January 2010 to February 2020. Thus, on average we have around 800 observations per month. Figure 2 shows that the number of observations is larger in recent years. This data excludes the time period of COVID-19 to avoid the discussion how this special time period influences our results. According to the literature, COVID-19 had a strong impact on stocks which represents the special nature of that time periods for both ESG and non-ESG related financial questions (e.g., Demers et al. 2021; Kökény, Kenesei, and Neszveda 2022).

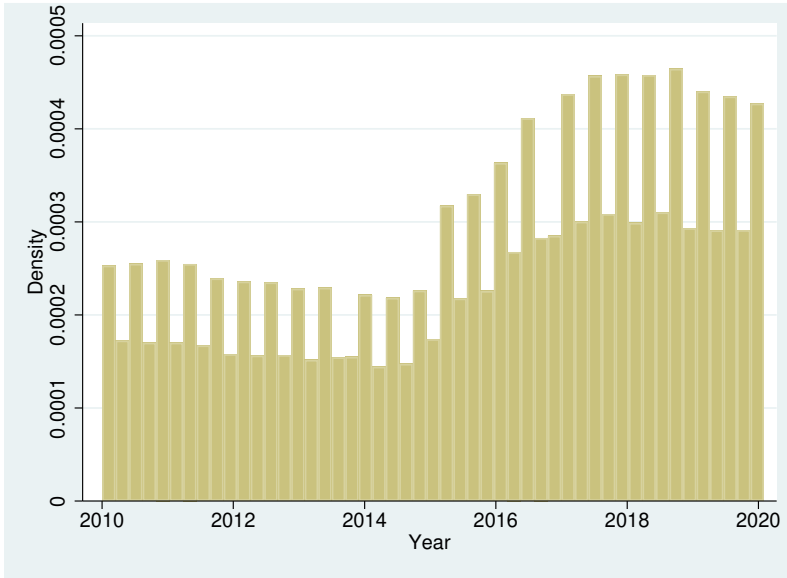


Figure 2. Monthly distribution of observations

2.3 Summary statistics

This section provides summary statistics on our most important variables: the ESG scores and the newly constructed gamma and weighted gamma measures. Table 1 shows that ESG scores take on values between 0 and 100. Generally *Environmental score* is lower relative to *Social* and *Governance scores*. Gamma and weighted gamma values have lower variation relative to ESG scores.

Table 1. Descriptive statistics of ESG scores and gamma

<i>Variable</i>	<i>Mean</i>	<i>Median</i>	<i>St. Dev.</i>	<i>Minimum</i>	<i>Maximum</i>
Environmental Score	28.59	21.14	27.34	0	98.55
Social Score	43.98	40.685	20.23	0.6	97.95
Governance Score	51.27	52.60	21.4	0.44	99.54
Gamma	0.0419	0.0437	0.001	0.0043	0.0616
Weighted gamma	0.0446	0.0448	0.0129	0.0036	0.0903

This table contains summary statistics of our most important variables over the period January 2010 and February 2020. Please note that *gamma* and *weighted gamma* mean and median are different from thresholds displayed in *Figure 4* and *Figure 5*. The mean and median represented on the figures were calculated using values from October 2008 to February 2020. To see more details why we analysed the period 2010–2020 see *Section 2.2*

Figure 3 shows that gamma and weighted gamma values are concentrated around the values 0.032,

0.039 and 0.045. Weighted gammas are slightly better distributed among the possible values, so the distribution peaks are smoother.

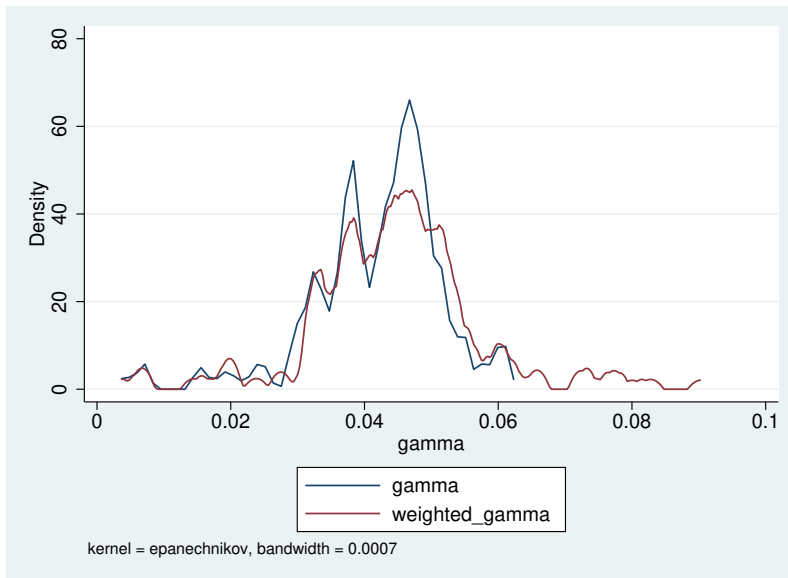


Figure 3. Distribution of gamma and weighted gamma

In *Figure 4* and *Figure 5* we see the time series plot of gamma and weighted gamma between 2010 and 2020. The mean and median values displayed in the figures are the thresholds used to define high and low intensity periods. The thresholds were calculated using gammas over the period October 2008 and February 2020, while in the analysis we only used 2010–2020 to examine our question. For this reason thresholds in *Figures 4, 5* and the mean, median shown in *Table 1* are different.

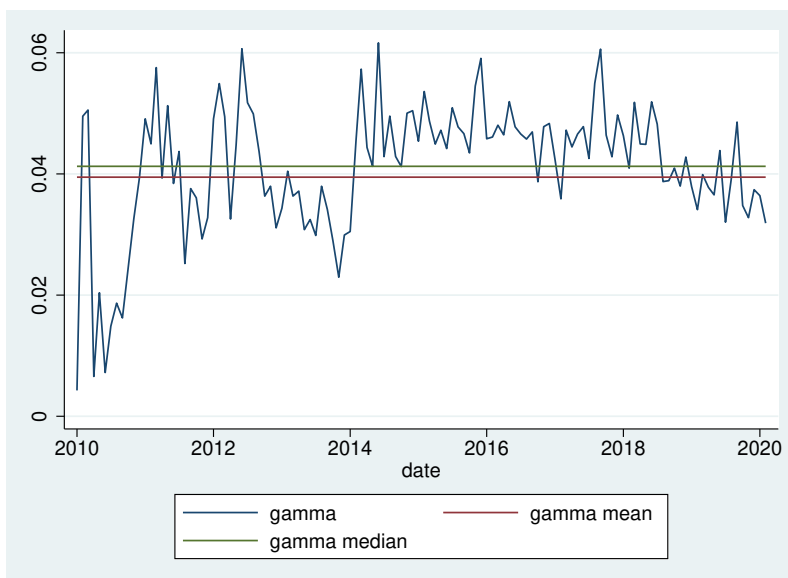


Figure 4. Monthly gamma (January 2010 - February 2022)

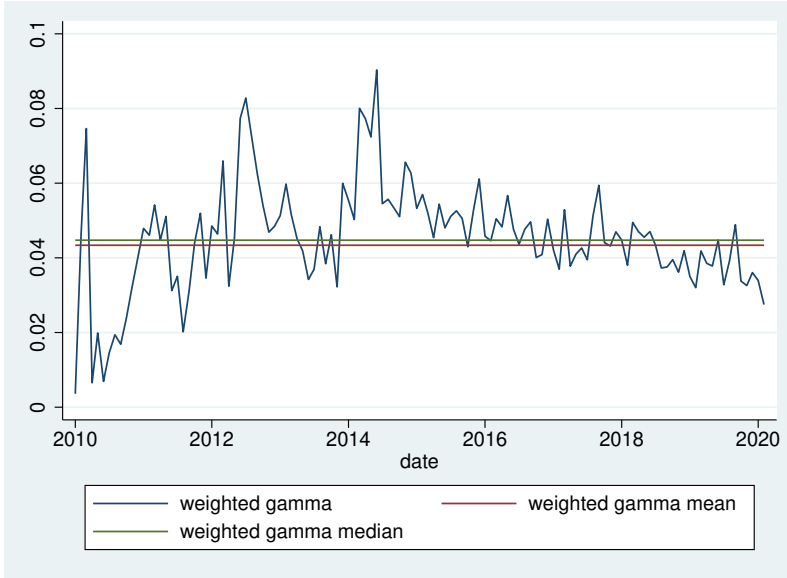


Figure 5. Monthly weighted gamma (January 2010 - February 2022)

Figure 6 displays that stocks in our sample generally have lower environmental scores, while higher governance scores. Around 20 there is a second spike in the distribution of environmental score. This might be incorrect data, however we could not identify any data cleaning step followin which the suspicious spike disappears.

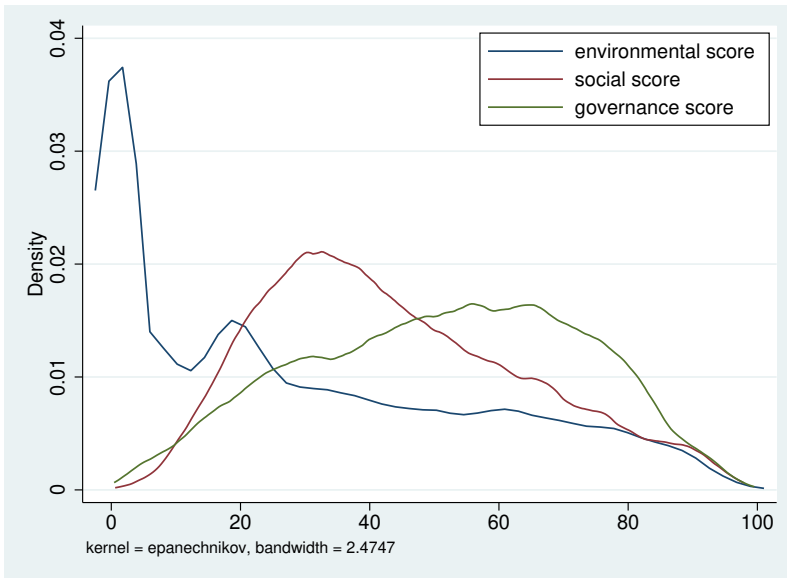


Figure 6. Distribution of ESG scores

3. Methodology

This section presents the applied methodologies in detail. Firstly, we describe Structural Topic Model methodology used to identify the intensity of media coverage of environmental issues. Second, the

paper illustrates the process of Fama-MacBeth regression. There are several empirical approaches to investigate the relation between a characteristic such as an ESG score and expected returns (Mérő, Nagy, and Neszveda 2020). The standard portfolio based approaches (e.g., Neszveda and Vágó 2021; Neszveda and Simon 2021;) or alternative portfolio based approaches (e.g., Fain and Naffa 2019; Naffa and Fain 2022) has the advantage that it does not assume any linear relation and it reduces noise, however these approaches have the disadvantage of losing information by creating portfolios compared to Fama-MacBeth regressions. Furthermore, Fama-MacBeth regressions are stricter in controlling for other known characteristics related to expected returns. As a consequence, in this paper, we apply Fama-MacBeth regressions to test our main hypothesis.

3.1 Structural topic model

The contribution of our study to the literature is that it measures the impact of the frequency of green topics in the news on financial markets. The first step in such a methodology is to generate a time series that quantifies the green intensity. For this purpose, we use the topic model.

The topic model is a commonly used unsupervised machine learning tool that identifies topics based on the pattern of occurrence of words in text data. The most common algorithm among topic models is Latent Dirichlet Allocation (LDA). The general concept of this is that every topic occurs in a certain proportion in every text, and every topic is a mixture of words (Blei, Ng, and Jordan 2003).

LDA is a mathematical method to find the associated words, sort them into topics, and estimate the proportions of these topics in the documents (news in our case). As a result, we can derive several coefficients to each word, which shows the probability that is generated from a given topic.

The number of topics is a hyperparameter of the model. Too few topics will produce results that are overly broad, and it is impossible to interpret, while choosing too many will result in the "over-clustering" of a corpus into many small, highly-similar topics" (Greene, O'Callaghan, and Cunningham 2014, p. 498). Similarly to clustering methods, there are rules to determine the optimal value of this parameter, for example semantic cohesion and exclusivity (Bischof and Airolidi 2012). We estimate the model with several number of topics (from two to 30 for each even value), but use the one with the smallest number of topics and containing one in a clearly identifiable way related to environment / pollution. The proportion of that topic in the news on a given day can be used to extend the general Fama-MacBeth regression. The reason is that if we use a model not having enough topics, then the environmental topic will be mixed with something else, while a model with too many topics would require additional effort to correctly aggregate the environmental topics (we also checked the model with significantly higher number of topics, but we did not observe appearance of multiple environmental topics.).

The general approach of Structural Topic Modelling (STM) is very similar to the LDA, but it also uses metadata information about the documents. The proportion in which each topic contributes to a document is called topic prevalence. With the structural topic model, the prevalence can vary along the metadata. This causes that while the expected topic proportion in the LDA is equal for each topic, but not in the STM.

Following Cerchiello and Nicola (2018) and Dybowski and Kempa (2020) we extend the topic model with time covariance, which means that the prevalence of the topic varies over time, and some topics may go out of fashion while others start trending. A spline function is used on the number of days since the first article, to ensure that non-linear effects can also be captured. This also results that the prevalence of topics may not be equal.

The first step to run STM model is to assign a corpus (a collection of words in an ordered form) from the investigated text. Here we follow the framework of Roberts, Stewart, and Tingley (2019). As it is a commonly used approach, we omit numbers, stopwords (e.g. and, or, the) from the corpus and we stem the words (remove the "s", "tion" and others from the end of the word). We estimate the model with several number of topics, from 2 to 30 for each even value, since the runtime is still

two days².

To identify each topic, we use the words that are most likely to come from that topic. The probability of the occurrence of topics in a given article is estimated by the model, and the occurrence of each topic in relation to nature / global warming is averaged for a given monthly intensity of the green topic (γ). At this point, we assume that an article does not carry more weight just because it is longer, so we do not aggregate based on the number of words.

3.2 Fama-MacBeth regressions

We first run the following time series regression on future return for all stocks to get each stock's $i \in \{1, \dots, I\}$ exposure to the $m \in \{\text{BETA, SIZE, BTM, MOMENTUM, ENVIRONMENTAL SCORE, SOCIAL SCORE, GOVERNANCE SCORE}\}$ variables.

$$R_{i,t} = \alpha_i + \hat{\beta}_{i,F_1} \cdot F_{m=1,t} + \dots + \hat{\beta}_{i,F_m} \cdot F_{m,t} + \varepsilon_{i,t} \quad (4)$$

Using the estimated betas from the first step, we run the following cross-sectional regression in each month $t \in \{1, \dots, T\}$ to check whether stocks with higher values of the m factor do yield higher returns.

$$R_{i,t} = \gamma_t + \gamma_{T,m=1} \cdot \hat{\beta}_{i,F_1} + \dots + \gamma_{t,m} \cdot \hat{\beta}_{i,F_m} + \varepsilon_{i,t} \quad (5)$$

To estimate m factor's risk premium, we take the average of the individual factor risk premium we found in each period.

$$\hat{\lambda}_m = \frac{\sum_{t=1}^T \hat{\lambda}_{t,m}}{T} \quad (6)$$

The estimate of the error term is the average of errors we found in each time period.

$$\hat{\varepsilon} = \frac{\sum_{t=1}^T \hat{\varepsilon}_t}{T} \quad (7)$$

Standard error of the respective factor's risk premium is the standard deviation of the estimated risk premium divided by square root of T .

$$\sigma(\hat{\lambda}_m) = \frac{\sigma(\hat{\lambda}_{t,m})}{\sqrt{T}} \quad (8)$$

4. Results

Structural Topic Model subsection presents the environmental topic we found in our news data, show the words typically occurring in the topic and cite some articles belonging to the topic. The following subsection contains the results we found with Fama-MacBeth regressions.

4.1 Structural Topic Model

Running the structural topic model with a different number of topics, we found that an environmental topic appears at 14 topics first³. The topic proportions are demonstrated in Figure 7, the environment related topic is the second one. As an evidence Figure 8 shows the words that are most likely to have been generated from topic 2.

2. CPU: Apple M1 pro (10 cores), RAM: 17.2.

3. The outcome of the other models can be found in the related GitHub repository: <https://github.com/MarcellGranat/green-finance-news/blob/main/result.md>.

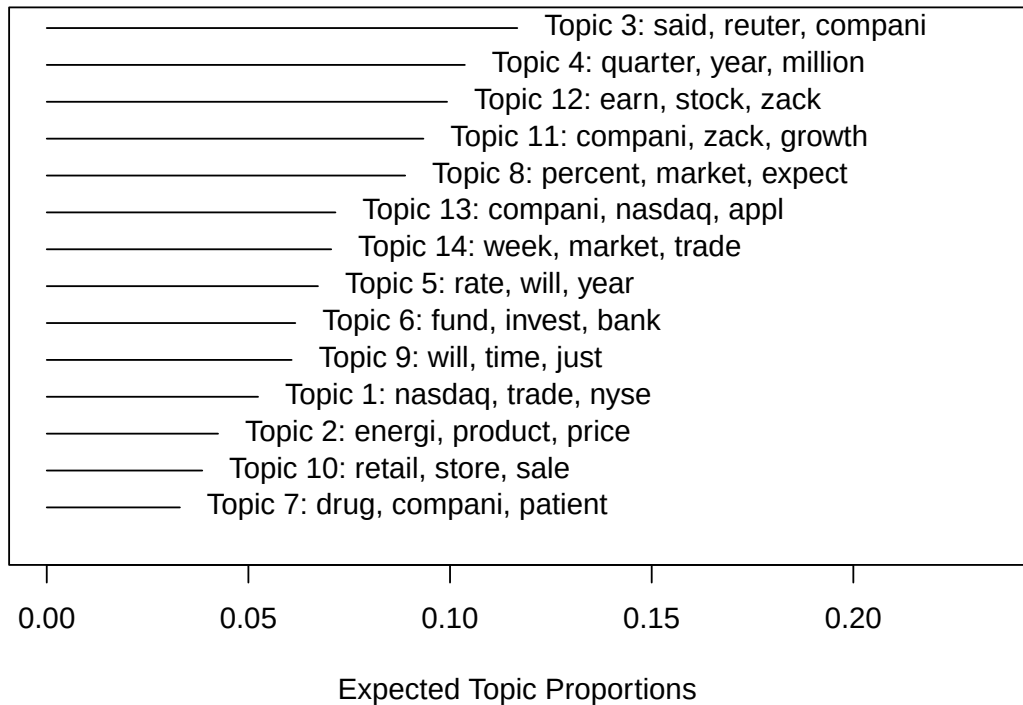


Figure 7. Estimated topic proportions.

Examining the texts containing the highest estimated proportion of topic 2 by the model are also apt to confirm our assertion that the occurrence of these topics is a good measure of the intensity of the green topic in the news. Three listed in the following as examples.

"Exxon Mobil NYSE XOM says it is restarting its 560K bbl day Baytown Tex refinery second largest in the U S six days after it was shut because of **heavy rain from Hurricane** Harvey Phillips 66 NYSE PSX says it is preparing to resume operations at its Sweeny refinery and its Beaumont terminal in Texas its Pasadena refined products terminal is resuming truck loading for **gasoline** this afternoon while operations at its **Gulf Coast fractionation plant** in Mont Belvieu are suspended Also Occidental Petroleum NYSE OXY has loaded and shipped its first **crude oil** cargo from its Western Gulf Coast terminal at the Port of Corpus Christi since Harvey"

"Exxon Mobil NYSE XOM has made its seventh major **oil** discovery in the Stabroek block offshore Guyana following drilling at the Pacora 1 exploration well partner Hess NYSE HES reveals Pacora resources will be integrated into the third phase of development at the Guyana project helping bring production to more than 500K bbl day of **oil** Hess says The Pacora 1 well discovery adds to previous world class discoveries at Liza Payara Snoek Liza Deep Turbot and Ranger 1 which are estimated to total more than 3 2B recoverable **oil** equivalent **barrels** XOM is operator of the 6 6M acre Stabroek block and holds a 45 while Hess owns 30 and Cnooc s NYSE CEO Nexen has 25"



Figure 8. Word cloud display of the enviromental topic.

"Petrobras NYSE PBR subsidiary In Bolivia and the country s state run YPFB Chaco have signed a 1 2B agreement to explore two **natural gas** fields with potential reserves of 4T of the Bolivian government says The fields are Astillero and San Telmo in southern Bolivia YPFB has a 40 stake in San Telmo and PBR has 60 while PBR owns 40 in Astillero and YPFB has 60 Both fields are expected to begin **producing gas** in 2022"

It can be seen that the topics discussed contain terms mainly related to the energy sector: *energy, nature, barrell, nuclear, chemical, mine*. We use the proportion of this topic in the articles to proxy the media's attention towards environmental issues.

4.2 Fama-MacBeth regressions

In this chapter we examine whether the effect of ESG scores is different when environmental issues receive more media coverage. To check this, we run Fama–MacBeth (Fama and MacBeth 1973) regressions on different subsamples. First, we run regressions using observations in months when environment received high media coverage. These months will be referred to as intensive periods. Then, we use observation in months when environmental issues were less intensively presented in the media. These months will be referred to as non intensive periods. Our hypothesis is that ESG scores will have a significant effect on future returns in periods of high-intensity, whereas no predictive power in periods of low-intensity media coverage.

We control for the variables in the Carhart four-factor model. (Carhart 1997) Namely to the respective stock's market beta, size, book-to-market ratio, and momentum.⁴

We define intensive periods of environmental media coverage in the following four ways:

4. Data section details how these variables are created

1. $\gamma > \gamma_{mean}$

Figure 4 shows which 73 months are identified as intensive periods based on this criterion. (Table 2 – 2nd column) The remaining 49 months are the non-intensive periods. (Table 2 – 3rd column)

2. $weighted\ \gamma > weighted\ \gamma_{mean}$

Figure 4 shows which 67 months are identified as intensive periods based on this criterion. (4th column) The remaining 55 months are the non-intensive periods. (5rd column)

3. $\gamma > \gamma_{median}$

Figure 5 shows which 72 months are identified as intensive periods based on this criterion. (6th column) The remaining 50 months are the non-intensive periods. (7th column)

4. $weighted\ \gamma > weighted\ \gamma_{median}$

Figure 5 shows which 67 months are identified as intensive periods based on this criterion. (8th column) The remaining 55 months are the non-intensive periods. (9th column)

We summarise our results in Table 2. Column 1 shows that over the period of January 2010 to February 2020 *Environmental Score* had no significant impact on stock returns. However, *Social Score* were associated with an average monthly return of 0.0062% (Newey–West t-statistic: 2.27), while *Governance Score* decreased future returns c.p. on average with -0.004% (Newey–West t-statistic: -2.45).

These results suggest that stocks with higher *Social Score* outperform firms with lower social indicator value. Whilst, firms with higher *Governance Score* have lower future returns than those with a lower score. The direction of relationship between these scores and future returns does not change between intensive and non-intensive periods.

Environment Score and *Governance Score* have a negative, while *Social Score* has a positive impact on future returns. This suggests that different ESG scores are considered differently by investors. Also these results might be driven by investors' different perceptions of different industries. To analyse this question one should group stocks into sectors and focus on how ESG scores change among industries. However, this is beyond the scope of this research. Overall, we obtain a rather mixed picture, which is in line with Cao et al's (Cao et al. 2020) results. They find ESG score to have an impact on specific industries, while no effect on others. But even in the sectors which ESG was significant they generally find a negative relationship.

Despite ESG coefficients being statistically significant, the average return is much lower for ESG scores compared to the other factors. Our results are similar to previous studies focusing on US market that used the Fama–MacBeth regression methodology. (Timár 2021) This shows that investors do not value sustainability to such extent that its impact can be considered economically significant. (Ashwin Kumar et al. 2016) Although, it is important to mention, that we do not focus on coefficients on their own, rather how they change in intensiver periods relative to non-intensive months.

We find that in periods of intensive environmental media coverage *Social Score* and *Governance Score* significantly affect future returns, while in low-intensity periods they have no explanatory power. These findings are robust to different definitions of intensive and non intensive periods. Moreover, we find that using median as a threshold to define high-intensity periods all of the ESG pillar scores significantly predict future returns.

Also, our findings show that in intensive periods the average of the coefficients of *Environmental Score* is -0,0049, while in non-intensive periods the average of the beta's is -0,0017. The effect is almost three times bigger in intensive periods relative to non intensive months. Despite the difference in the magnitude of effect, *Environmental Score* is not significant in most of the settings.

These result implies that investors pay attention to ESG scores when environmental issues receive high media coverage. But in months when investors are less confronted with environmental problems in the press they do not take these issues into account in their investments.

In *Column 1* we run FM regressions using every observation in months between January of 2010 to February 2020. In *Columns 2 to 9* we run FM regressions using observations from 12 months that meets given criteria. For instance in *Column 2* we use months in which y was higher than y_{mean} . This way there are gaps in the time series in *Columns 2 to 9*. *Averageage* shows the estimated coefficients, *NW-t-statistics* shows Newey–West t -statistics with 12 months lag, while *NW-p-value* shows corresponding p -value. *BETA* is monthly beta. *SIZE* is the logarithms of the stocks' market capitalization, *BM* is the logarithm of the firms' book-to-market ratio, while *MOM* is the momentum: the average return over last year. *ENVIRONMENT SCORE*, *SOCIAL SCORE* and *GOVERNANCE SCORE* show weighted average relative ESG ratings of a company.

[illegible]

5. Conclusion

This paper examined the relationship between ESG scores' affect on future returns and the intensity of media coverage of environmental issues. We assessed the importance of environmental issues in media with machine learning based Structural Topic Modelling (STM) methodology. Then we ran Fama-MacBeth (Fama and MacBeth 1973) regressions using observations in months when environmental issues recieved higher than average (lower than average) media coverage. We found that in intensive topic periods (using median as a threshold) ESG scores significantly affect future returns, while in low-intensity periods they have no explanatory power. These result suggest that investors pay less attention to firms' attitude towards sustainability when they see less articles related to environmental issues. However, when environmental issues receive high media coverage investors take ESG scores into consideration. Generally, we find a negative relationship between *Environmental score* and future return, irrespective of media's attention towards climate change. This contradicts the idea that investors value sustainability. However, it is important to mention that we did not take into account that ESG scores' impact might differ between industries and also ignored that retail traders might assess ESG scores differently than institutional investors. Hence our results are not intended to measure the magnitude of the effect, but how the effect varies with media attention.

Our research has three important limitation. We adopt gamma's and weighted gamma's statistical measures of central tendency (mean, median) to define intensive and non-intensive periods. We used monthly gamma and weighted gamma values over the period October 2008 to February 2020 to assess mean and median. However, this information only became available as time progressed. Thus, we calculate media intensity in period t using information which was not yet available in that month. This method was neccessary beacuse we did not have any prior knowledge about which gammas should be considered relatively high or low.

Secondly, we do not give an answer as to who is causing the phenomenon we have found. Previous research found that capital market anomalies are amplified by the presence of small investors. (e.g. (Csillag and Neszveda 2020)) Choi et al. (Choi, Gao, and Jiang 2020) also find that retail investors' (not institutional investors') ESG trading patterns are exposed to extreme weather in their location. This study did not examined whether our finding was fueled by increased retail investor attention to global warming in periods of intensive media coverage.

Also, this study did not seek to find out what causes the deviation in the media coverage of environmental issues. However, to truly understand the connection between our *gamma* and ESG scores one must answer that question. Based on our results this might be a reasonable next step. The paper of Choi et al. (Choi, Gao, and Jiang 2020) suggest that extreme weather might grab press attention, resulting in more intensive media coverage of environmental issues. However, as our news data source is investment specific it might be less exposed to this effect. Also, certain events may also affect the intensity of the environmental topic, such as energy, environmental regulation and weather related events. Moreover, further research could analyse how media intensity affects ESG scores in different sectors. Another interesting question could be whether media intensity impacts low-emissing "green" stocks and high-emissing "brown" stocks.

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