

Green Sentiment in Financial Markets: A Global Warning

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Abstract

We use textual analysis to measure the growing concern about environmental issues and to assess its impact on stock prices in the United States. Using a dataset of 71,785 articles published in *The Wall Street Journal* from 2010 to 2019, we create several scores capturing media coverage of environmental news and investigate their influence on S&P500 constituents. We find a significant impact on the stock returns of one third of firms in the sectors exposed to environmental risks. An assessment of the results at company level shows that this impact is related to their environmental performance. The results are robust to the use of alternative lexicons and weighting schemes, various specifications and sample periods.

JEL Classification: G12, G14, Q53, Q54.

Keywords: environmental finance, climate change, investor sentiment, media coverage, textual analysis.

1 Introduction

The terms ‘climate change’ and ‘global warming’ are ubiquitous in the worldwide media. The number of articles in the top five US newspapers containing these words reached a milestone in September 2019, with about 800 articles per month compared to 100 in the early noughties.¹ The current media focus on environmental issues has raised public awareness and given economic actors a strong incentive to engage in more eco-friendly

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¹See http://sciencepolicy.colorado.edu/icecaps/research/media_coverage/usa/index.html. The five journals are *The Washington Post*, *The Wall Street Journal*, *The New York Times*, *USA Today*, and *Los Angeles Times*.

practices. The financial markets have not been spared from this upheaval. Climate finance flows reached a record high of USD 612 billion in 2017, double the amount in 2013 (Climate Policy Change [2019]).

This paper measures media coverage of environmental problems and assesses its potential impact on financial markets. For this purpose, we use a dictionary-based approach and measure the frequency of environmental terms in media text. Given the lack of a reference lexicon on climate issues, it was necessary to compile a new dictionary to extract environmental sentiment. Several dictionaries are used to parse financial texts, in particular the ones developed by Loughran and McDonald [2011] and Bodnaruk, Loughran and McDonald [2015]. However, these lexicons, which are employed to gauge the tone of articles relative to general economic or financial market conditions, are not relevant to our specific context. Therefore, we generate our own lists of words with a Wordnet-based algorithm. We start out from three existing lexicons on environmental issues (the thesauruses provided by Cambridge and Macmillan and a glossary released by environmental organisations) and use a recursive algorithm to expand them with synonyms and antonyms.

Using these new lexicons, we develop media coverage scores for environmental issues with a *bag of words* approach. The indices are extracted from 71,785 financial and economic articles published in *The Wall Street Journal* between 2010 and 2019. We retrieve green scores by computing the relative frequency of articles containing environmental terms, as well as the number and relative frequency of environmental terms per article. The articles are either equally weighted or are assigned a higher weight when they are on the front page of the newspaper or their title contains an environmental term. This methodology yields 27 alternative scoring rules. The green scores computed from the sample documents reflect media coverage of environmental conferences, the announcement and implementation of new environmental regulations in the United States and several extreme weather events. A correlation analysis with other economic, financial and political sentiment variables, available on the main data providers, illustrates the new content of the sentiment variables introduced in this paper.

We then examine stock market reactions at the time of newspaper releases to the use of the environmental terms, by investigating whether green scores have an impact on US weekly stock returns. An extensive firm-level analysis is conducted on 494 constituents of S&P500. As an empirical framework, we use the five-factor asset pricing model of Fama and French [2015] augmented with the environmental news measures. Time-series analysis is performed for each individual stock to evaluate the dependence of asset returns on the environmental news score. Since our corpus of articles originates from the economic and financial sections of a business newspaper, our scores are likely to influence investment decisions. Pro-social investments can be motivated by the pro-environmental preferences of the asset manager or asset holder, social prestige and signalling, as well as material incentives such as laws and taxes penalizing polluting firms (Bénabou and Tirole [2006] and Bénabou and Tirole [2010]). An increased attention to environmental issues in the media could accentuate these three factors.

The estimation results over the past decade show that one third of stock returns in sectors exposed to environmental risk are sensitive to media coverage of climate events. We also find that investors are more sensitive to news released on the front page of the newspaper. The response of stock returns varies across sectors according to their environmental performance. Not surprisingly, the impact is found to be negative in energy and in materials such as chemicals and metals, suggesting that the latter are perceived as highly polluting activities by investors. Conversely, stock returns are positively related to the score in real estate, which could be related to the recent development of eco-labeling in this market. A positive impact is also perceived for electric utilities, where there has been a general switch from coal to less polluting sources of energy over the past decade in the United States. Such results are useful to predict the impact on individual stock prices of environmental news. In the context of increased attention to climate change risk, these results could help portfolio managers in their asset allocation.

These findings are robust to the use of alternative samples and specifications. We find very similar results over various sub-samples. Considering only the stocks priced over the whole period or over the last five years does not affect the estimation results. We estimate

different versions of the Fama-French model and obtain similar findings. We also consider the impact of local news and find that certain sectors are more responsive to worldwide events, even though the overall significance rate does not change. Finally, the use of a state-dependent model shows that investors are more responsive to media coverage of environmental news in *bull markets*. The latter result suggests that during financial downturns, investors are less inclined to discriminate between the stocks of polluting firms and those of more environmentally-friendly companies in their asset allocation. Overall, we confirm the impact of green sentiment on financial markets, with a stronger effect in bull markets and for global news in several sectors.

Our paper relates to several strands of research. First, it is closely connected to the literature using textual analysis to assess the link between media sentiments and stock prices. From the seminal paper by Tetlock [2007] onwards, several papers have studied the impact of the tonality of various text sources (newspapers and social media platforms) on stock features such as returns, trading volumes and volatility; e.g. Garcia [2013], Fraiberger, Lee, Puy and Ranci re [2018] and Schnaubelt, Fischer and Krauss [2020]. This literature generally shows that media pessimism leads to downward movements on market prices followed by a reversal to fundamentals. Garcia [2013] and Fraiberger et al. [2018] also show that this effect is larger in unfavorable periods (recession or bear markets) and Fraiberger et al. [2018] point out that the impact of local news is smaller and transitory. We depart from this literature by extracting an environmental sentiment rather than an economic sentiment. Likewise, Engle, Giglio, Kelly, Lee and Stroebel [2020] develop several climate news series through textual analysis of newspapers; however, their purpose is to construct portfolios that hedge innovations in these series.

Our paper also contributes to the behavioral finance literature pointing to the effect of pro-social or pro-environmental preferences on investments. Using a natural experiment among individual investors in an online bank, D skeland and Pedersen [2016] show that environmental concerns play a role in the investment decision, even though financial motives remain predominant. Riedl and Smeets [2017] use survey and experimental data to show that investors' social preferences together with social signaling, although to a

lesser extent, are the main reasons why individuals hold Socially Responsible Investment (SRI) equity funds. Hartzmark and Sussman [2019] present evidence based on a natural experiment demonstrating that investors view sustainability as a positive attribute; the publication of sustainability ratings by Morningstar in 2016 led to net inflows to the funds with the highest ratings and net outflows from those with the lowest ratings. Using a matching method on a set of 110 green bonds, Zerbib [2019a] finds a small but significant yield that investors are willing to relinquish in order to invest in green assets rather than in conventional bonds with the same level of risk. Establishing a link between our green sentiment index and US stock returns depending on the environmental footprint of the firms, is consistent with these results.

Finally, this paper is related to the literature on the link between the Environmental, Social, and Governance (ESG) performance of firms and their asset returns. Several theoretical papers show that the returns of high polluting firms are expected to be higher; e.g. Baker, Bergstresser, Serafeim and Wurgler [2018], Hsu, Li and Tsou [2020], Pastor, Stambaugh and Taylor [2019] and Zerbib [2019b]. In particular, Hsu et al. [2020] develop a general equilibrium model in which high emission firms' profitability and thus asset prices are negatively affected by policy shifts in environmental regulation. Accordingly, investors demand higher expected returns as risk compensation. Pastor et al. [2019] put forward another general equilibrium model with green and brown firms and a continuum of agents trading firm shares with different sustainability preferences. Agents with environmental preferences obtain extra utility from holding green stocks and expected returns of firms decrease with ESG stock performance. In both papers, however, green assets outperform brown assets in the event of environmental shocks such as unexpected shifts in environmental regulation (Hsu et al. [2020]) or in the ESG concerns of investors and customers (Pastor et al. [2019]). Therefore, realized excess returns are negatively affected by environmental shocks in transition phases. This paper illustrates this dynamic by showing a negative impact of environmental news on the returns of the less eco-friendly firms.

The remainder of the paper proceeds as follows. The second section describes the

method applied to retrieve green sentiment indices from media text. The third section introduces the empirical framework used to assess the impact of green sentiment on financial markets and presents the estimation results at firm and sector levels. Additionally, we provide several robustness checks of the results. The last section concludes.

2 Environmental media indices

This section describes the method used to measure green sentiment from media text. We present our text sources, our environmental dictionary and the extraction of green scores.

2.1 Text sources

To retrieve environmental sentiment from media text, we use a selection of articles published in *The Wall Street Journal* (WSJ) and archived in *Factiva*.

The WSJ is a US business-focused daily newspaper published six days a week. It was launched in July 1889 and has been in print ever since. There is also an online version that is accessible to subscribers only since 1996. WSJ is one of the two national newspapers in the United States, the other being *USA Today*. WSJ is the most widely read bought American newspaper. In 2019, the newspaper sold 2.83 million copies daily, of which 1.83 million were digital-only subscriptions.² The journal has an excellent reputation among investors and the influence of WSJ articles on financial markets is clear in many studies; see among others Tetlock [2007], Tetlock, Saar-Tsechansky and Macskassy [2008], Ahern and Sosyura [2015], Manela and Moreira [2017] and Madsen and Niessner [2019].

Given the recent concern for environmental issues, the articles collected cover the past decade only, from January 2010 to March 2019 in the Factiva database. Like Fraiberger et al. [2018], we focus on two subject categories in Factiva: 1) Commodity/Financial Market News and 2) Economic news, the content of which is more likely to influence investment decisions. We remove identical duplicates pointed out by Factiva. In doing so, we obtain 71,785 articles and a total of 26,354,812 words.

²<https://www.statista.com/statistics/193788/average-paid-circulation-of-the-wall-street-journal/>.

To present our corpus of articles more precisely, Figure 1 depicts the evolution of the number of articles per year. The left-hand graph depicts the number of articles in the section on the commodity/financial market or economic news and the right-hand graph the total number of articles in WSJ. We note a decrease in the number of articles released per year over the decade. However, as shown in the right-hand graph, this decline is not specific to the articles published in the commodity/financial market or economic news.

2.2 Dictionary

To measure the coverage of environmental issues by WSJ, we first need to create a lexicon. To do so, we use either terms related to environmental issues provided by English dictionaries or glossaries compiled by environmental organizations. We expand the original lists with an algorithm searching recursively for antonyms and synonyms. Finally, a *stemmization* of each word in the list serves to capture all possible inflections in the text. These three phases are described below.

We started from existing glossaries on environmental issues to generate our new dictionary. To our knowledge, there is no unique reference list for environmental terms. For the sake of robustness, we consider several glossaries. The first lexicon that we provide relies on the Cambridge Thesaurus and the second one on the Macmillan Thesaurus for ‘environmental issues’. The third one is based on a glossary of environmental terms that pools lists of terms provided by the US Environmental Protection Agency (EPA), the European Environment Agency and the Irish Environmental Agency. The Cambridge thesaurus contains 158 words, the Macmillan thesaurus 84 words and the glossary of the environmental agencies 137 words.³ By using initial glossaries on environmental issues, we compile wordlists that are not restricted to climate change issues. We assume that news on oil spills, pesticides or consumer waste also has an impact on asset portfolio management in favor of non-polluting industries.

³For the Cambridge thesaurus, see <https://dictionary.cambridge.org/topics/the-earth-and-outer-space/environmental-issues/>, <https://www.macmillandictionary.com/thesaurus-category/british/environmental-issues> for the Macmillan thesaurus and <http://www.epa.ie/footer/a-zglossaryofenvironmentalterms/> for the lexicon of the environmental agencies.

In a second step, to avoid omitting potentially related words, we use an algorithm to track synonyms and antonyms for each term in the three lists. A recursive search is done for each word in the list with *WordNet* (a thesaurus developed in Princeton University) as long as new synonyms or antonyms appear, e.g. reusable and reclaimable for recyclable. Several terms with an exponential number of synonyms or antonyms are discarded and reinstated individually in the final list, e.g. pollution, contaminate or spillage. At the end of this process, we also remove words that are likely to be used with different meanings in other contexts, e.g. dumping, population or poison.⁴ Additionally, several misleading words have been transformed into less ambiguous phrases; for instance green is replaced by green funds, green bonds, green power, green energy, green product, green tech, etc.

In a third step, each term in the list is reduced to its root form (*stemmization*) to account for the different forms of the same word present in the text. For example, we use ‘ecolog’ instead of ‘ecological’ in the Cambridge and Macmillan lists to include words like ecology, ecologist, ecological, ecologically, etc. in the search. Finally, we add to the three resulting lists 34 names of the main environmental organizations (worldwide organizations, US governmental agencies and the major non-governmental organizations⁵) and their acronyms. To evaluate the relevance of the final lists, we manually check the use of each word in a sub-sample of 10% of the articles selected randomly from our database.

Overall, we compile a list of 147 terms for the Cambridge-based lexicon, 113 terms for the one from the Macmillan thesaurus and 178 terms for the one from the environmental agencies glossary (the three final lexicons are reported in Appendix 1). In the following, we refer to these three lists as the ‘Cambridge’, ‘Macmillan’ and ‘EPA’ lists. The wordlists cover the three dimensions of environmental risk on investors’ portfolio companies discussed by Krueger, Sautner and Starks [2020]: physical, technological and regulatory risks. The three lists contain terms related to extreme weather events and

⁴11 words are discarded and reinstated individually in the Cambridge-based list, 9 in the Macmillan one and 6 in the environmental agencies list. 27 words with an ambiguous meaning are excluded from the first list, 18 from the second one and 12 from the third list.

⁵See https://en.wikipedia.org/wiki/List_of_environmental_organizations for worldwide organizations and US agencies and <https://guides.lib.berkeley.edu/c.php?g=496970&p=3427176> for non-governmental organizations.

physical changes of the planet (e.g. climate change), technological innovations (e.g. fuel efficient, electric vehicles) and regulatory changes (e.g. carbon tax, emission allowance).

Some preliminary statistics on the use of the terms in the three wordlists are provided in Figures 2 and 3. Over the whole period, 9.4% of the articles in our corpus contain at least one word belonging to one or more of the three dictionaries, 1.7% of the articles are published on the front page and 0.6% contain one or more environmental word/s in the title. This proportion is quite stable over time, as shown in Figure 2. The frequency of each word is also stable. Figure 3 reports the most frequent words in our three lists in the WSJ articles, either over the whole period (2010-19) or over the last five years (2014-2019). The most employed words generally appear in two or three of the lexicons, showing the global coherence of all three lists. The results point to the overall stability of the ranking over time. The five most frequent words (environmental, EPA, climate change, renewab and pollut) are the same for the two periods. However, three words (oil spill, green energy, fuel efficient) drop out of the top list over the most recent period. Instead, there is an increase in the frequency of green bond, ozone and landfill over 2014-2019, in line with the growing concern for sustainability in finance, consumption and waste management.

2.3 Environmental scores

Using the three dictionaries, we derive several measures to capture media coverage of environmental issues. The first score is simply based on the frequency of articles in our corpus containing at least one term from our wordlists. The computation of the second and third scores relies on the *bag-of-words* approach, which is the most common method for measuring text tone. This approach consists of counting the frequency in the articles of the terms in our dictionary, regardless of grammar and word order in the document.⁶ In the following, i is the index for the article, d the index for the day and l is a subscript designating the dictionary.

⁶Alternative methods rely on supervised machine learning. They involve splitting the corpus of text and training the algorithm on a pre-classified part of the dataset. This approach is not considered here since the classification of the documents is not obvious in our context.

To obtain the first score, we parse each article in our database and check whether it contains at least one environmental term from a lexicon:

$$ENV1_d^{(l)} = \frac{1}{N_d} \sum_{i=1}^{N_d} \omega_i \mathbf{1}_{i,d}^{(l)}(environment) \quad (1)$$

with N_d the total number of articles published on day d , $\mathbf{1}_{i,d}^{(l)}(environment) = 1$ if article i published on day d contains at least one word from lexicon l and 0 otherwise and ω_i the weight of article i , as defined below. Dividing the sum by the number of articles is important to cancel the effect of the variation in the volume of articles published over time (as seen previously in Figure 1).

One can defend that articles using environmental terms several times should be more influential on the environmental sensitivity of investors than the ones that only mention the word once. In the second score, to give more importance to the former, the dummy variable is replaced by the number of environmental words in each article. The score is as follows:

$$ENV2_d^{(l)} = \frac{1}{N_d} \sum_{i=1}^{N_d} \omega_i NE_{i,d}^{(l)} \quad (2)$$

where $NE_{i,d}^{(l)}$ denotes the number of environmental words from lexicon l in article i published on day d . The importance of article i in the score increases with the number of environmental words. If all articles mention environmental words only once, the first two scores will be identical.

In the third score, we take into account the length of the article, which is calculated as the proportion of environmental words in each article:

$$ENV3_d^{(l)} = \frac{1}{N_d} \sum_{i=1}^{N_d} \omega_i \frac{NE_{i,d}^{(l)}}{NW_{i,d}} \quad (3)$$

where $NW_{i,d}$ is the number of words in article i . For the computation of the length of the article $NW_{i,d}$, we first remove the stopwords, e.g. a, the, is, are, and, but, etc., in each article of the corpus and we then count the remaining words. This is done with the *Natural Language Tool Kit* (NLTK) package of Python. To filter out the stopwords, we

use the list of English stopwords provided by the toolkit (179 words).

We consider alternative weights ω_i for article i in the three scores.⁷ In the first scheme, the articles are equally weighted; $\omega_i = 1$. In the second scheme, a higher weight is given to a front-page article:

$$\omega_i = \begin{cases} \log\left(\frac{N}{FP}\right) & \text{if article } i \text{ is published on the front page} \\ 1 & \text{otherwise} \end{cases} \quad (4)$$

with N the total number of articles in our corpus and FP the number of articles published on the front page of the WSJ. Here, we follow Fedyk [2018] who shows that front-page positioning of news on the Bloomberg terminal leads to much higher trading volumes and larger absolute price changes in US equity securities. Conversely, the incorporation of non-frontpage information is much slower. Even though the difference is higher in the hours following the news publication, the effect of positioning is found to be statistically significant several days after publication.

Finally, our last weighting scheme is designed to overweight articles with a strong focus on environmental problems. We consider that this is the case when an environmental term appears in the title and a higher weight is given to the article:

$$\omega_i = \begin{cases} \log\left(\frac{N}{T}\right) & \text{if article } i \text{ has an environmental word in the title} \\ 1 & \text{otherwise} \end{cases} \quad (5)$$

where T denotes the number of articles containing an environmental word in the headline. This weight is especially high since very few articles mention environmental issues in their title (164 out of 71,085). Likewise, Thomson Reuters news analytics (TRNA) provides a relevance score for documents alongside the sentiment score of companies, assessing the extent to which the parsed text concerns the company. The relevance score depends on

⁷While we may assign different weights to the articles, we treat every term in our dictionaries as equally important. In the literature on media sentiment, it is usual to give more weight to uncommon words with an Inverse Document Frequency (TF-IDF) weighting of words. This weighting scheme is not appropriate in our context, since our lexicon contains very technical terms, e.g. biome, bionomic, biotic, which are only seldom used and would be overweighted in the scores.

the number of times the company is mentioned in the text and is set at its maximum value when the firm is mentioned in the headline.

Overall, we have 27 alternative environmental news measures (3 scores \times 3 weighting schemes \times 3 dictionaries). To get weekly measures, we average the daily values of each score to the weekly level. Table 1 provides descriptive statistics for our environmental scores (mean, median, standard deviation). To check that our scores actually reflect environmental sentiment and do not proxy uncertainty variables in entire financial markets or markets only specific to the energy sector, with some of them also being derived from media text, we also assess the correlation of our scores with several uncertainty measures, namely the economic policy uncertainty index EPU, the CBOE VIX index, and the CBOE Energy Sector ETF Volatility Index VXXLE. The daily variables are converted to a weekly frequency with averages of the observations during the week, for comparison with our scores computed with the news over the whole week. Low and rarely significant correlation is found with the environmental measures developed in this paper (the correlation is at most equal to 17%), which shows their new content with respect to general measures of uncertainty.

The correlation analysis in Table 1 also includes the two climate news series developed by Engle et al. [2020] through textual analysis of newspapers. Their first score is based on the comparison of the text content of the WSJ each month and a fixed corpus of environmental texts published by various organizations. The second score is computed as the percentage of articles from various media sources containing the phrase ‘climate change’ and that have been assigned to a negative sentiment category by a data analytics vendor.⁸ Due to the availability of the data, our correlation analysis is done at the monthly frequency until June 2017 for the first climate news series and until May 2018 for the second one. Not surprisingly, the correlation is positive and generally significant but the scores developed in the paper still show distinct variations (correlation at most equal to 45%). Engle et al. [2020] focus on news related to climate change, since their

⁸The two series constructed by Engle et al. [2020] were taken from Johannes Stroebel’s website at <http://pages.stern.nyu.edu/~jstroebe/>.

purpose is to constitute climate change hedge portfolios. In this paper however, we are seeking to assess the impact of media coverage of environmental news not exclusively related to climate change, and for this purpose, we rely on a lexicon with a larger scope, as described previously.

Figure 4 depicts one of the sentiment indices over the whole sample period: ENV2 computed from the EPA dictionary and with uniform weights (other weighting schemes yield similar patterns). The index shows clear spikes at *Conferences of Parties*, especially the Paris COP 21 in November 2015. Trump's Paris Agreement withdrawal announcement in June 2017 does not pull the index up, but there is a peak the following month. Other peaks are related to new regulations by EPA, e.g. the EPA carbon reduction plan (the Clean Power Plan defines new standards in the electric power sector to cut carbon dioxide emissions; it was first announced by EPA in June 2014 and its final version was disclosed by president Obama in August 2015). We also note a high level of the index when major environmental disasters occur, such as the Fukushima Daiichi nuclear disaster in March 2011, Hurricane Sandy in October 2012 or, more recently, the Californian wildfires in November 2018. These events received heavy media attention, including in the economic section of WSJ. Their coverage in the media should affect positively the environmentally-friendly firms and negatively the carbon-intensive ones.

3 Measuring market reaction to media coverage of environmental issues

Since our news-based environmental indices are extracted from the economic and financial sections of a business-focused newspaper, they are likely to affect the environmental sensitivity of investors and influence their decisions. This section describes the empirical design used to assess this impact and reports the market response from constituents of S&P500. Several variants are then considered to explore the robustness of the results.

3.1 Empirical design

Media coverage of environmental issues can act as a catalyst for green investment through several channels. As illustrated by a survey conducted among institutional investors by Krueger et al. [2020], investors may consider climate risks in portfolio arbitrage for financial and nonfinancial reasons. Incorporating environmental issues into the investment decision may be viewed as improving portfolio returns and reducing their risks. For instance, carbon-intensive firms may be penalized when climate regulations and policies are implemented and media coverage of these new policies and regulations could draw investors towards companies promoting more responsible strategies on climate change. As for nonfinancial motives, a growing body of the literature shows that pro-environmental preferences can lead to growing investment in the assets of environmental-friendly firms, and more generally, of those with the highest ethical standards; e.g. Døskeland and Pedersen [2016], Riedl and Smeets [2017], Hartzmark and Sussman [2019] and Zerbib [2019a]. Media coverage of extreme weather events could promote such decisions.

To assess this impact, we incorporate the environmental scores in the widely used Fama-French five-factor equation (Fama and French [1993], Fama and French [2015]):

$$R_t - R_{f,t} = \alpha + \beta_1(R_{m,t} - R_{f,t}) + \beta_2SMB_t + \beta_3HML_t + \beta_4RMW_t + \beta_5CMA_t + \beta_6ENV_t + u_t \quad (6)$$

where R_t is the stock return of the firm in week t , $R_{m,t} - R_{f,t}$ is the excess return on the market (value-weight return of all CRSP firms incorporated in the US and listed on the NYSE), SMB_t is Small Minus Big factor, HML_t is High Minus Low, RMW_t is Robust Minus Weak, CMA_t is Conservative Minus Aggressive. The variable ENV_t is the environmental score derived in the previous section and u_t the residual term. In order to investigate the impact of environmental sentiment on financial markets, we study the significance and the sign of the coefficient β_6 . In doing so, we measure a potential influence of the green sentiment on the stock returns, when controlling for the market, size, value, gross profitability and investment factors.

Note that many authors have tried to identify new risk factors in such an empirical

setting. Harvey, Liu and Zhu [2016] mentioned 316 different factors and classed them in several categories. Our environmental score belongs to the same behavioral sub-category as the sentiment factor proposed by Baker and Wurgler [2006]. The Fama-French equation has also been used to identify positive abnormal returns for companies with higher ESG performance; e.g. Edmans [2011], Eccles, Ioannou and Serafeim [2014] and Li, Minor, Wang and Yu [2019].

We run time-series regressions to estimate equation (6) for each S&P500 constituent and assess each stock exposure to the environmental factor. Weekly returns are collected from January 2010 to March 2019 from Bloomberg. They are derived as the log-difference of asset prices on two subsequent Fridays.⁹ We retain only the asset prices available from January 2017 at a minimum. Among the 494 remaining stocks, 436 stocks are sampled over the whole period. The fact that 58 stocks are available over a shorter period could be detrimental to the comparability of the results obtained for each company, so we check this point in the robustness part. The five factors of Fama and French [2015] are taken from the website of Kenneth French.¹⁰ Overall, we run 494 time-series regressions. Each equation is estimated by OLS and we apply Newey West (1987) robust standard errors to autocorrelation and heteroscedasticity in the residuals up to 5 lags.

To investigate whether the results are sector-specific, we use the GICS categorization (2018) of the industry, to which all S&P500 companies are assigned. This ranking comprises 11 sectors: energy, materials, utilities, industrials, real estate, financials, communication services, information technology, health care, consumer discretionary and consumer staples. Huynh and Xia [2020] show that the bond exposure of firms to climate change news risk diminishes with their environmental performance. Accordingly, we expect the impact of our sentiment index to differ across firms in these sectors.

In the *energy* sector, the green score should have a negative impact on stock returns.

⁹The WSJ is published Monday to Saturday, while stock markets are closed on weekends. This means that the impact on financial markets of news published on Saturday would only occur the week after. To account for this delayed impact, the green score of week t is derived from the daily values of the score from the Saturday of week $t - 1$ to the Friday of week t .

¹⁰The last two factors are only available at a daily or monthly frequency. We chose the daily factors and converted them to the weekly frequency by taking the last value for each week.

The environmental impact of the oil and gas industry is mainly negative. In addition to the damage caused by oil and gas exploration and production on wildlife and nature, fossil fuel combustion is responsible for about 76% of greenhouse gas emissions and 93% of CO₂ emissions in the US, according to EPA data in 2017. Hence, environmental news should urge investors to reduce the share of this sector in their portfolios and should additionally have a negative impact on the stock prices of these companies. However, this negative effect may be counterbalanced by a ‘sin stock premium’ for the expected return (Hong and Kacperczyk [2009]), or by the predominant position of the United States in oil production and therefore by the high profitability of the firms in this sector.

Concerning the *utility* sector, the firms in the sample mainly operate in the electricity field, as well as in gas (1 firm) and water (1) distribution. Even though fossil fuels still play a significant role in generating electricity in the US, there has been a drastic shift from coal to natural gas as well as a significant increase in renewable energy.¹¹ This phenomenon has lowered emissions of carbon dioxide and other forms of pollution over the past decade. Increasing the share of renewable energy sources might also increase the profits of utilities, as discussed in Acemoglu, Kakhbod and Ozdaglar [2017] and Falbo, Pelizzari and Taschini [2019].¹² Hence, a positive impact of our green score could be expected on returns in this sector. Obviously, this assumption should be assessed at the firm level according to the share of coal, petroleum or renewable energy resources used to produce electricity. If investors distinguish between these different forms of production, the positive impact would be stronger for firms using geothermal, hydroelectric, solar and wind energies.

The *materials* sector includes polluting industries such as chemicals (14 firms), metals and mining (3), construction materials (2) and reputedly less polluting companies such

¹¹The share of coal in the net generation of electricity dropped from 49% in 2007 to 28% in 2018, while the share of natural gas increased from 22% to 36% and the share of renewable energy from 10% to 18% (EIA, 2019).

¹²Theoretically, Falbo et al. [2019] describes the conditions under which utilities make a higher profit when increasing the share of renewable energy and pricing the electricity generated at the higher marginal cost of fossil fuel production. Acemoglu et al. [2017] also show that electricity producers with a diverse energy portfolio can raise their markups by strategically dropping their conventional energy supplies when renewable energy supply is on the up.

as containers and packaging, paper products (6). The chemicals group includes fertilizer and pesticide producers, industrial gas or other agriculture-related chemical producers, together with plastics, synthetic fiber producers, etc. The returns of the most polluting firms in this sector could be affected negatively by the green score. For instance, the profit of a firm in fertilizers and pesticides could be penalized by new worldwide regulations on toxic products (e.g. restrictions on the use of glyphosate-based herbicides) and by the increase in organic farming (US organic sales increase regularly and exceeded \$50 billion in 2018, which is 6% of food sales in 2018). In light of these developments, one would expect a significant and negative coefficient in this sector.

The *real estate* market is changing and part of its recent evolution is related to issues of energy efficiency. As evidence of this change, many standards have been introduced to evaluate the environmental performance of buildings; e.g. the Energy Star provided by EPA and the Leadership in Energy and Environmental Design (LEED) certification awarded by the US Green Building Council. A sharp upward trend is visible in the number of certifications: in 2018, more than 41% of commercial space in the 30 largest US office markets obtained at least one of the two green labels, compared to only 5% in 2005. The positive impact of green certifications on the financial performance of buildings (rent, occupancy rate and transaction price) is well-documented in the literature; see among others Eichholtz, Kok and Quigley [2010] for single homes and Holtermans and Kok [2019] for commercial buildings. As pointed out by Eichholtz, Kok and Yonder [2012], the greenness of the real estate project positively affects the following three financial indicators: return on assets, return on equity and the ratio of funds from operations to total revenue. Therefore, a positive impact of the environmental score can be expected.

However, it may be more difficult to establish general results for *industrials*, *consumer discretionary* and *consumer staples*, given the substantial firm heterogeneity in these categories. The industrials sector consists of capital goods, commercial & professional services and transportation. In our sample, consumer discretionary comprises retailers of automotive parts and accessories, as well as consumer electronics. The impact of the environmental score on firms producing consumer staples could depend on the portion

of their activity based on organic food. In these sectors, it will be necessary to assess the results at company level. Finally, the last four sectors, (*financials, communication services, information technology* and *health care*) will constitute counterfactuals in our analysis; the environmental impact of the latter sectors is not perceived to be high, in contrast to oil exploration or chemicals production. Accordingly, we do not expect a strong link between returns in these sectors and our environmental news measure.

3.2 Estimation results

To describe the estimation results, we first investigate the overall significance of the environmental index in the Fama-French equation and identify the most influential score among the 27 alternative indices. Then we study the impact of green sentiment at sector and firm levels.

Overall results

In a first step, we discard the firms of the 4 counterfactuals sectors and focus on the remaining ones (consumer discretionary, consumer staples, energy, industrials, materials, real estate and utilities), that are likely to be affected by the environmental news index (275 stocks). Table 2 shows the percentage of significance at the 10% level of the environmental coefficient in the 275 time-series regressions (the estimation results for the 494 firms are provided in Appendix 2). These percentages are calculated from the t-statistics with a HAC correction. As described below, the results are supportive of the second score elaborated with the EPA lexicon giving more weight to front-page articles. In this case, more than one third of firms are impacted by the environmental news measure (versus 12% in the counterfactuals sectors and 25% in the full sample). This finding gives support to an impact of media coverage of environmental topics on financial markets.

Among the alternative indices, the number of environmental words per article (ENV2) is the most influential. By contrast, the percentage of significance of the first score (ENV1), which only measures the number of articles containing at least one environmental term, is two or three times lower. This means that if an environmental word is only mentioned in passing in a text largely about other issues, investor sentiment will be

unaffected. The more environmental words the article contains, the more likely it is to actually deal with environmental topics. Adjusting the term weighting according to the length of the article (ENV3) does not improve this result.

Overweighting environmental news in the title has a detrimental effect on the performance of the scores. However, this finding may be due to an insufficient number of articles in our corpus containing an environmental term in their title (164 out of 71085). The two other weighting schemes are relatively close. Assigning a higher weight to articles released on the front page slightly improves the results in most cases, e.g. 34.55% versus 34.18% for the second score constructed with the EPA dictionary. This means that news on the front page has a larger influence on investors, as previously shown by Fedyk [2018]. However, this improvement is only marginal; the effect might be lessened by a different layout of the web edition of the newspaper (in 2018, more than 60% of subscriptions to WSJ are digital-only).

Regarding the choice of dictionary, green scores based on the EPA lexicon are more influential. This lexicon overwhelmingly outperforms the two other dictionaries for all indices (e.g. 34.55% of coefficients are significant with front-page weights, compared to about 25% with the two other dictionaries). This result also holds with the two other weighting schemes (title or uniform weights). Therefore, using a lexicon made by environmental agencies improves the results compared with less specialized glossaries.¹³ Hereafter, we will focus only on the second score calculated using the EPA dictionary with either uniform or front-page weights.

Results by sector and by company

Table 3 shows the percentage of positive or negative coefficients of the environmental index in each sector with either uniform or front-page weights. As expected, we find a negative impact of our score in *energy* (100% of coefficients are negative but only

¹³Note that a reduced list consisting of the five most frequent environmental words or roots of words in Figure 3 (environmental, EPA, climate change, renewab, pollut) has a much lower performance. The environmental score is only significant in 24.36% of cases with front-page weights. Hence, using a relatively wide list of synonyms and antonyms related to the environment improves the results. Conversely, an extended lexicon that merges the Cambridge, EPA and Macmillan wordlists and contains 289 terms performs similarly (30.90% of coefficients are significant with front-page weights).

24% of them are significant with the front-page weight) and in *materials* (80% of the coefficients are negative and 32% are significant). As previously mentioned, the lack of significance in energy might be explained by the preponderance of the US in worldwide oil production. By contrast, the impact is overwhelmingly positive in *utilities* (77% of the coefficients are positive and significant) and in *real estate* (77% of the coefficients are positive and significant). As expected, the environmental index is far less significant in the counterfactual sectors: 12% of the coefficients in the *financial* sector, 10% in the *IT* sector and 11% in the *health care* sector. In *communication services*, the percentage is higher (17%) but the results are not comparable, since only two thirds of companies are priced over the whole period. When considering only the returns available from 2010 to 2019, the percentage falls to 12%, as shown later in the robustness part.

In the following, we investigate at a more micro level the estimates and t-statistics of the coefficients obtained with the EPA dictionary and front-page weights. Figure 5 plots the t-statistics of the environmental score in the augmented Fama-French equation for each firm, excluding those in the counterfactual sectors. In addition, Table 4 provides the coefficient and the R-squared of the equation when specifying the sector and subsector of each company (see Appendix 2 for all the estimation results).

In *energy*, 86% of negative and significant coefficients pertain to the sub-sector of oil and gas exploration and production, activities that could disturb land and marine ecosystems. The most significant coefficients also correspond to highly-polluting firms, according to the 2017 Newsweek green ranking of the 500 largest publicly traded companies in the United States.¹⁴ For instance, Phillips 66 ranks 384th (with a Newsweek score at 10%), Chevron Corp. ranks 223th (score at 37.7%) and ConocoPhillips ranks 208th (score at 39.2%).

The financial performance of *utilities* is positively related to the environmental score, in line with the overall increase in the share of green energy in electric (multi-)utilities

¹⁴The Newsweek green ranking is based on 8 criteria: combined energy productivity score, combined greenhouse gas productivity score, combined water productivity score, combined waste productivity score, green revenue percent range, sustainability pay link, sustainability board committee, audited environmental metric.

(24 out of 26 utility companies in the S&P500 are electric utilities). The environmental score is particularly influential for the highly virtuous companies in terms of share of renewable sources to produce energy and the related CO2 emission intensity.¹⁵ Duke Energy (highest t-statistic) has drastically reduced its share of coal in total net generation of electricity (from 58% in 2005 to 33% in 2017), and tripled the share of renewable energy over the same period through the development of wind energy. In line with this evolution, Duke is a constituent of the Dow Jones Sustainability North America index (DJSI).¹⁶ Consolidated Edison (coefficient significant at 1%) has increased its share of wind and solar energy to respectively 21% and 10% in 2017 (compared to 0% in 2005) and obtained the Energy Star award in 2018.¹⁷ Finally, Edison International (with the highest estimated coefficient and a significance at 1%) no longer uses coal in electricity generation for 2017 (versus 33% in 2005) and has replaced coal with hydroelectricity. Conversely, independent power producers & energy traders (AES corporation and NRG energy), which do not use renewable energy, display negative coefficients and NRG energy is affected significantly.

The negatively and significantly affected companies in *materials* produce chemicals (6 out of 14 firms) or metals (2 out of 3 firms). More precisely, 2 out of 3 firms in fertilizers & agricultural chemicals have a negative and significant coefficient: the Mosaic company with the highest negative t-statistic (Newsweek green score of 27.7%) and CF Industries Holdings Inc. A copper producer (Freeport-McMoRan Inc.) has the second highest negative t-statistic in this sector and has been ranked 13th by the Political Economy Research Institute among the 100 companies emitting airborne pollutants in the US.¹⁸ Among the firms in chemicals negatively and significantly affected by the environmental index, LyondellBasell Industries holds 7th position in the same ranking, while for steel,

¹⁵We use the information provided in the ESG/sustainability quantitative reporting template. See <https://www.eei.org/issuesandpolicy/finance/Pages/ESG-Sustainability.aspx>.

¹⁶The Dow Jones Sustainability North America index is a stock index calculated from the top 20% of the largest 600 stocks in the S&P Global Broad Market Index according to their ESG practices.

¹⁷This recognition of the highest level by EPA honors ‘groups of businesses and organizations that have made outstanding contributions to protecting the environment through superior energy efficiency achievements’.

¹⁸The ranking of 2016 based on data from 2014 is available on <https://www.peri.umass.edu/toxic-100-air-polluters-index-2016-report-based-on-2014-data>.

Nucor Corporation is in 35th position. By contrast, none of the six firms in the metal & glass containers and paper packaging subsectors are affected by our environmental score. Within the entire *materials* sector, only one firm (Flavors & Fragrances) responds positively and significantly to the score; in 2018, this firm was awarded an A ranking by the Carbon Disclosure Project for water security and climate change.

As previously stated, the *real estate* sector is highly responsive to environmental media coverage; 77% of coefficients are positive and significant, with 13 out of 31 coefficients significant at 1%. Over the past decade, the proportion of green-certified buildings has increased steadily. This trend makes real estate more profitable, as shown in the literature, and could explain the positive reaction to the green index in this sector. Alexandria Real Estate Equities obtains the highest t-statistics. Alexandria's total annual rental revenue from LEED projects amounts to 53% of its total revenue and the company is aiming for all its new ground-up development projects to obtain LEED gold certification by 2025. Our results are also consistent with the composition of the DJSI: 6 out of 8 constituents in real estate display a significant and positive coefficient at least at the 5% level.

Finally, we examine the results in the last three sectors. In *consumer staples*, the environmental coefficients are significant in 34% of cases and the significant coefficients are systematically positive except for one firm. For the other companies, the positive influence of the environmental score may be partly related to the development of organic food in the US. Most significant and positive coefficients are found in Brewers and Distillers & Vinters, 3 out of 3, and in Packages Food & Meats, 6 out of 12. In beverages, Constellation Brands, which is affected significantly and positively by the environmental index, has been 'certified sustainable' by the California Sustainable Winegrowing Alliance (CSWA). Note also that DJSI comprises 6 food companies and the coefficient of the environmental score is positive for all of them in our regressions and significant for 5 of them.

The *consumer discretionary* sector is also most often influenced positively. However, the coefficient of the green score is only significant for 10 firms out of 62. Among the significant ones, Lowe's Cos in retailing is one of the largest five additions in the DJSI (ranked by Float Adjusted Market Capitalization as per 31 July 2019). Ford also shows

a significant coefficient at the 10% significance level; this finding could be related to the strategy announced by Ford to achieve both a majority of its overall sales from electric cars by the end of 2022 (Newsweek global ranking of 79). Among the positively affected firms, there is also 2 firms out of 10 in Apparel, Accessories and Luxury Goods and 2 out of 4 in the hotel sub-sector. Conversely, no firm is impacted in the two subcategories Casinos & Gambling and Restaurant (0 out of 2 and 0 out of 5 respectively).

In the last category, *industrials*, the results are more contrasted, with 19% of significant coefficients, generally at the 10% significance level, with positive and negative signs. In contrast to the automobile subsector, industrial machinery construction is impacted negatively (2 firms out of 3 in Construction Machinery & Heavy Trucks, 1 firm out of 1 in agricultural machinery). These firms have a poor environmental performance according to the 2017 Newsweek ranking (e.g. Caterpillar in 365th position with a green score of 14.4% and Deere & Company in 297th position with a score of 25.1%). Conversely, Republic Services, the activity of which is related to the environmental domain (solid waste collection, transfer, disposal, recycling, and energy services), has a positive coefficient.

3.3 Robustness tests

We explore the sensitivity of our results to alternative sub-samples and specifications. For each variant, Table 5 reports the percentage of significant green scores for all firms and per sector. The benchmark cases discussed above appear in the first two columns and are obtained with the EPA lexicon and either uniform or front-page weights.

We check the robustness of our results to the sample period. Our dataset contains 58 stocks that are not sampled over the whole period 2010-2019. While all stocks in real estate and utilities are traded from 2010 to 2019, this is the case for only two thirds of stocks in communication services. This may be harmful to the comparability of sectors. To address this issue, we restrict the sample to only the 436 stocks available since January 2010. The results in column (3) of Table 5 show a decrease in the percentage rate in communication services, which are a component of the counterfactual group (17% to 12%). The other sectors are not affected. As an alternative check, we repeat the

analysis for all available stocks over a shorter period of time, January 2014 to March 2019. The results appear in column (4). The main picture does not change, even though the overall significance percentage in the sample excluding the counterfactuals diminishes (27% compared to 35%). This decrease is mainly due to a smaller impact in energy and real estate.

As an alternative to the five-factor equation in the previous subsection, we consider the seminal CAPM model and the three-factor version of the Fama-French equation (Fama and French [1993]) in columns (5-6) of Table 5. The results are in line with the previous ones. The significance rate is similar with the CAPM model and there is a slightly higher rate in the three-factor equation (37%). The results by sector are essentially the same. To address a possible concern about the correction of residual autocorrelation, we next check whether our results are robust to the number of lags in the Newey West correction. In the previous analysis, we provide standard errors robust to heteroskedasticity and autocorrelation in the residuals up to five lags. We assess the robustness of the results to the lag order, with either a shorter (1 lag) or a longer (up to 12 lags) possible autocorrelation. The results in columns (7-8) of the table are very close to the benchmark results.

Our last two robustness checks are related to the previous literature on media sentiment. In a study on the effect of media tone in 25 advanced and emerging countries, Fraiberger et al. [2018] show that when economic and financial news items are specific to a country, they have a smaller and less persistent effect on the returns of firms. We explore whether this also applies for environmental news. In column (9) of Table 5, we repeat our analysis on a corpus of articles that exclusively focus on the United States. To gather the restricted set of articles, we use the region code for each article in Factiva and identify that 55.42% of articles do not cover any other area in the world. The overall significance result does not differ largely on this restricted sample, with 30% of coefficients significant compared to 35% for all geographical areas, but interestingly enough, the significance rate increases in real estate while it is much lower in energy. This finding suggests that investors in real estate are more sensitive to local news, while the energy

sector is more affected by worldwide events.

Finally, Tetlock [2007], Garcia [2013] and Fraiberger et al. [2018] show that the effect of economic and financial news is state-dependent, investors being more sensitive to news tone in economic or financial downturns. In the same way, investor sensitivity to environmental issues could depend on the state of the market. To identify market phases, we use a Markov-switching model of excess returns on the market (see Maheu and McCurdy [2000] or Maheu, McCurdy and Song [2012] for a similar approach). We estimate a two-state Markov-Switching AutoRegressive model with a switching intercept and variance, and identify a low-return volatile state (labeled as the bear market) and a high-return stable regime (interpreted as the bull market). We classify the observations as bull markets if the smoothed probability of the high-return and less-volatile state exceeds 50%. In doing so, 78% of observations are ranked in the bull state. We then allow a switch of the intercept and the coefficient of the environmental score according to the state in the augmented Fama-French equation.¹⁹

The results given in column (10) suggest a slightly higher sensitivity to environmental news when there is no crisis: 27% of coefficients are significant in bull markets compared to 21% in bear markets. In bear markets, the correlation of asset prices increases because they are driven by a strong common downward dynamic. Conversely, in bull markets the correlation decreases, while the dispersion of prices grows. Thus, investors can better discriminate in their asset allocation between stocks of polluting companies and those of more environmentally-friendly firms. This difference is particularly strong in the energy sector (38% of coefficients are negative and significant in bull markets compared to only 3% in bear markets) and in real estate (58% versus 35%). In materials, utilities and industrials, investors react in the same way to media coverage in the two states. These results contrast with economic news, the impact of which is concentrated on unfavorable periods, according to Garcia [2013] and Fraiberger et al. [2018].

Overall, the robustness checks confirm the results of the previous subsection. Environmental sentiment matters in financial markets. This finding is robust to the use of

¹⁹The results are very similar when we allow a change of all the coefficients of the model.

alternative samples and specifications. Interestingly, a smaller sensitivity is also found during financial downturns and as a response to local news in several sectors.

4 Conclusion

In this paper, we assess the sensitivity of financial markets to media coverage of environmental news. Using a dataset of 71,785 articles published in *The Wall Street Journal* from 2010 to 2019, we create several environmental scores to measure media coverage of environmental news. The score captures a broad set of events such as the implementation of new environmental regulations by EPA, the organization of environmental conferences, and several ecological disasters. To investigate a potential effect of environmental concern on financial markets, we consider Fama-French equations incorporating the environmental score. Our estimation results suggest that environmental media sentiment accounts for part of the variation in stock returns. The index is significant for more than one third of the firms more particularly exposed to environmental risks (and for 25% of the S&P500 constituents). The impact is negative in energy and materials. Conversely, stock returns are strongly positively related to the sentiment index in real estate and utilities. An assessment of the results at company level shows that the impact is related to their environmental footprint. We hope that these results would be a further motivation for firms to accelerate their green transition. In the context of growing concern about environmental issues, they could also be useful to portfolio managers when making their allocation choices.

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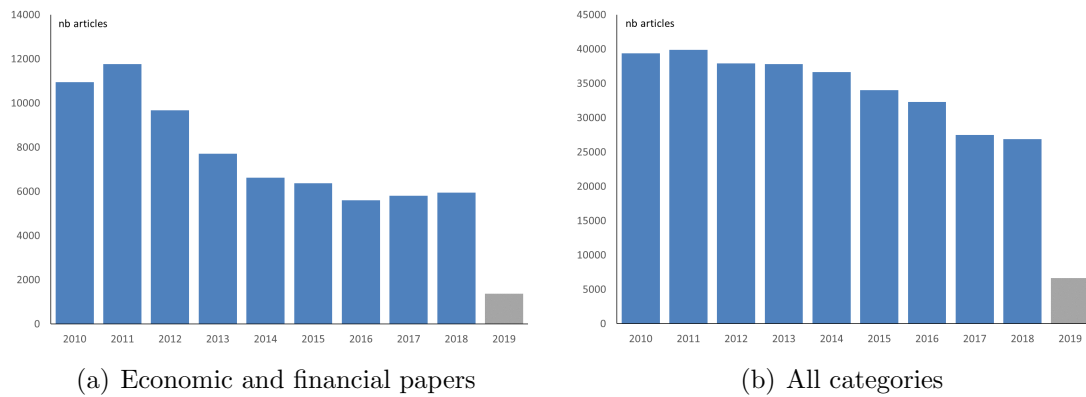
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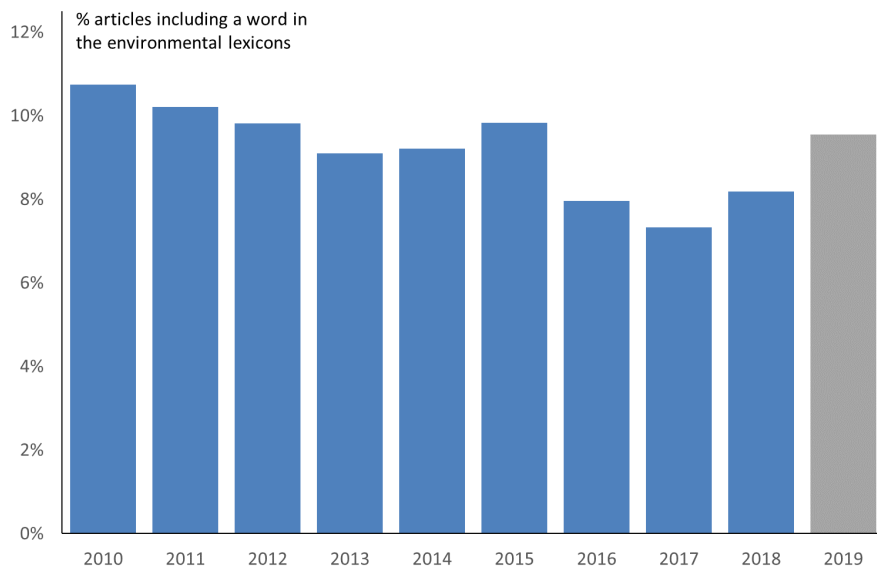
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Figure 1: Number of articles in *The Wall Street Journal*



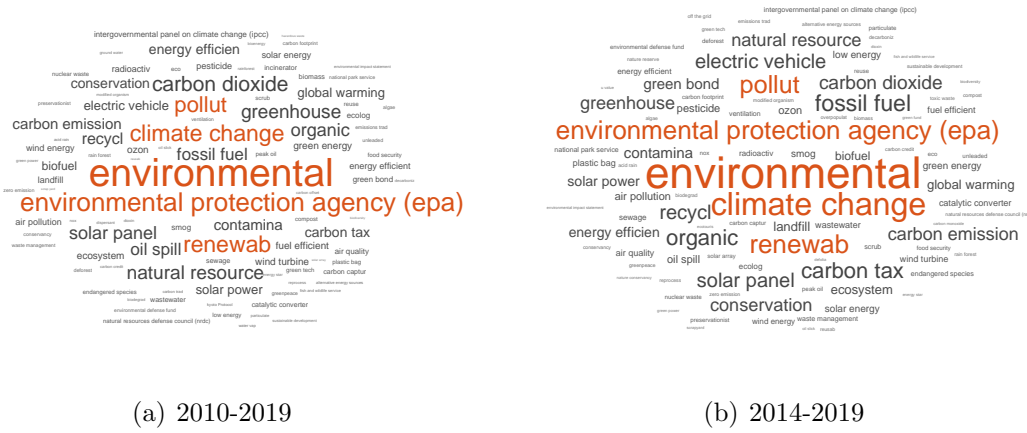
Note: This figure displays the number of articles published every year by the WSJ and referenced in the 'economic news' or 'commodity/financial market' section (graph on the left) or for all categories (graph on the right) in the Factiva database. In 2019, the number is calculated on articles released from January to March only.

Figure 2: Number of articles including a word from the environmental lexicons



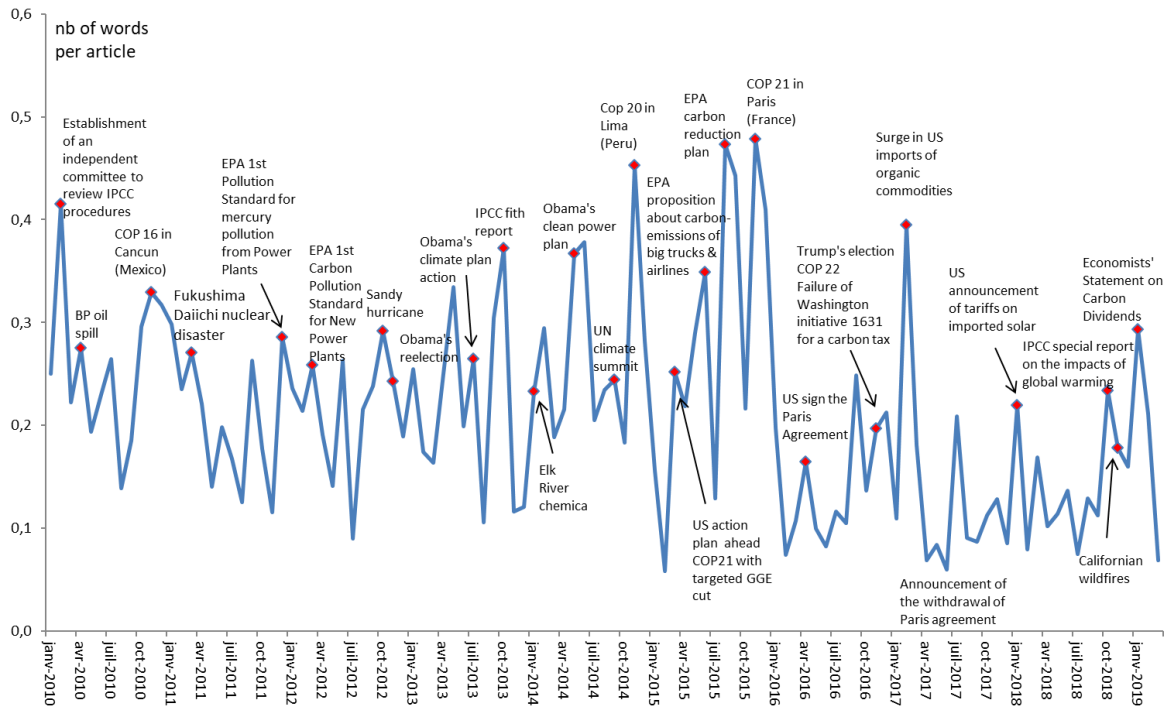
Note: This figure plots the proportion of articles published every year in our corpus that includes at least one word from the three environmental lexicons. In 2019, the number is calculated on articles released from January to March only.

Figure 3: Most frequent words in the corpus



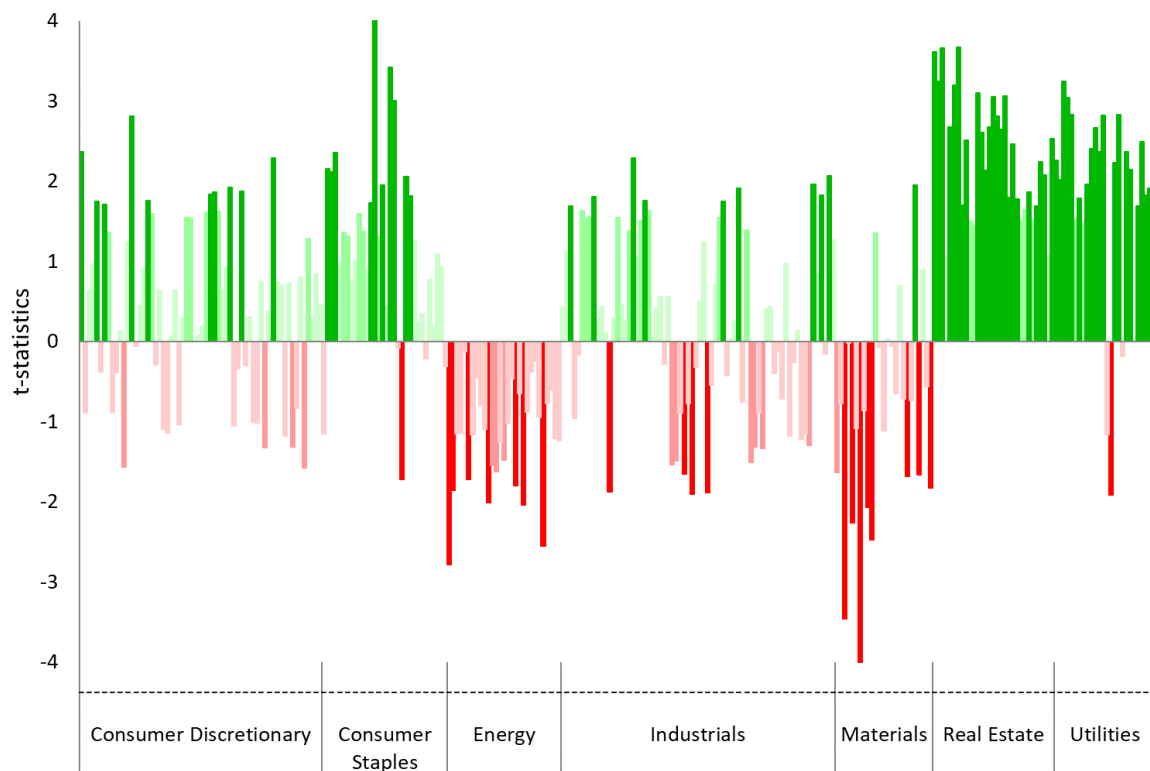
Note: This figure depicts the most frequent words of the three dictionaries in our sample of WSJ articles. The results are reported for 2010 to 2019 and 2014 to 2019.

Figure 4: Environmental score (2010-2019)



Note: This figure plots the monthly number of environmental words (EPA lexicon) per article (score ENV2 with uniform weights).

Figure 5: Significance tests of the environmental score



Note: This figure depicts the t-statistics of the environmental score in the augmented Fama-French equation for each firm in the sectors exposed to environmental risks.

Table 1: Descriptive statistics for the environmental scores

	Uniform weight											
	ENV1			ENV2			ENV3					
	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan
mean	0.075	0.063	0.057	0.238	0.210	0.183	0.0006	0.0006	0.183	0.0006	0.0006	0.0005
median	0.073	0.060	0.056	0.198	0.168	0.154	0.0005	0.0005	0.154	0.0005	0.0005	0.0004
25% quantile	0.057	0.045	0.042	0.131	0.101	0.092	0.0003	0.0003	0.092	0.0003	0.0003	0.0002
75% quantile	0.092	0.080	0.072	0.306	0.274	0.236	0.0008	0.0008	0.236	0.0008	0.0007	0.0006
Stand. Dev.	0.028	0.026	0.023	0.171	0.166	0.138	0.0004	0.0004	0.138	0.0004	0.0004	0.0003
ρ VIX	0.12***	0.13***	0.05	0.05	0.04	0.04	0.06	0.06	0.04	0.06	0.05	0.03
ρ VXXLE	0.09*	0.07	0.07	0.08*	0.06	0.07	0.06	0.06	0.07	0.06	0.03	0.05
ρ EPU	0.12***	0.17***	0.09**	0.02	0.04	0.01	0.05	0.07	0.01	0.05	0.07	0.03
ρ WJS	0.14	0.22**	0.26**	0.43***	0.45***	0.46***	0.39***	0.39***	0.46***	0.39***	0.46***	0.44***
ρ CHNEG	0.21**	0.11	0.26***	0.45***	0.39***	0.45***	0.42***	0.42***	0.45***	0.42***	0.37***	0.43***
	Front page weight											
	Title weight											
	ENV1			ENV2			ENV3					
	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan
mean	0.085	0.072	0.065	0.272	0.239	0.209	0.0007	0.0006	0.209	0.0007	0.0006	0.0005
median	0.083	0.069	0.063	0.223	0.186	0.166	0.0006	0.0006	0.166	0.0006	0.0005	0.0004
25% quantile	0.063	0.051	0.046	0.144	0.113	0.102	0.0004	0.0004	0.102	0.0004	0.0003	0.0003
75% quantile	0.105	0.090	0.080	0.343	0.312	0.272	0.0009	0.0009	0.272	0.0009	0.0008	0.0007
Stand. Dev.	0.032	0.030	0.027	0.201	0.196	0.165	0.0004	0.0004	0.165	0.0004	0.0004	0.0004
ρ VIX	0.11**	0.12***	0.04	0.05	0.04	0.04	0.06	0.06	0.04	0.06	0.05	0.03
ρ VXXLE	0.09*	0.06	0.06	0.08*	0.05	0.07	0.06	0.06	0.07	0.06	0.03	0.05
ρ EPU	0.11**	0.17***	0.09*	0.02	0.04	0.01	0.04	0.04	0.01	0.04	0.07	0.02
ρ WJS	0.15	0.21**	0.28***	0.41***	0.43***	0.44***	0.38***	0.38***	0.44***	0.38***	0.45***	0.43***
ρ CHNEG	0.21**	0.10	0.24**	0.43***	0.37***	0.43***	0.40***	0.40***	0.43***	0.40***	0.36***	0.41***
	Title weight											
	Title weight											
	ENV1			ENV2			ENV3					
	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan	Cambridge	EPA	Macmillan
mean	0.093	0.081	0.071	0.465	0.436	0.344	0.0012	0.0012	0.344	0.0012	0.0012	0.0009
median	0.087	0.073	0.064	0.274	0.233	0.175	0.0007	0.0006	0.175	0.0007	0.0006	0.0005
25% quantile	0.064	0.050	0.047	0.139	0.110	0.096	0.0004	0.0003	0.096	0.0004	0.0003	0.0003
75% quantile	0.115	0.105	0.089	0.590	0.601	0.449	0.0016	0.0016	0.449	0.0016	0.0016	0.0012
Stand. Dev.	0.044	0.042	0.036	0.531	0.527	0.415	0.0014	0.0014	0.415	0.0014	0.0014	0.0010
ρ VIX	0.11**	0.09**	0.04	0.02	0.01	0.02	0.03	0.03	0.02	0.03	-0.01	0.03
ρ VXXLE	0.06	0.03	0.05	0.04	0.02	0.03	0.02	0.02	0.03	0.02	-0.01	0.02
ρ EPU	0.10**	0.14***	0.08*	-0.03	0.02	0.00	0.01	0.04	0.00	0.01	0.04	0.04
ρ WJS	0.17	0.21**	0.27***	0.31***	0.20*	0.30***	0.31***	0.26**	0.30***	0.31***	0.26**	0.32***
ρ CHNEG	0.26***	0.19*	0.31***	0.38***	0.29***	0.33***	0.40***	0.33***	0.33***	0.40***	0.33***	0.37***

Notes: This table reports the mean, median, first and third quartiles, the standard deviation of the weekly environmental scores and their correlation with the CBOE VIX index (ρ VIX), the CBOE Energy Sector ETF Volatility Index (ρ VXXLE), the Economic Policy Uncertainty index (ρ EPU), and the WSJ Climate Change News indices developed by Engle et al. [2020] (ρ WJS and ρ CHNEG). Significance levels: *** if the correlation is significant at a 1%, ** at a 5%, * at a 10% level.

Table 2: Percentage of significance for the environmental index

Weight	Score	Cambridge dictionary	EPA dictionary	Macmillan dictionary
Uniform weight	ENV1	7.27%	11.27%	7.64%
	ENV2	<i>28.36%</i>	34.18%	<i>27.27%</i>
	ENV3	23.27%	32.00%	18.18%
Front page weight	ENV1	8.00%	8.72%	8.00%
	ENV2	<i>26.18%</i>	34.55%	<i>24.73%</i>
	ENV3	22.55%	32.72%	17.82%
Title weight	ENV1	8.72%	16.36%	9.82%
	ENV2	<i>20.00%</i>	25.45%	<i>17.45%</i>
	ENV3	14.18%	18.91%	14.91%

Notes: This table reports the percentage of significant environmental scores in the sample of stocks excluding the counterfactuals (275 stocks). The significance is assessed at a 10% level. The results are provided for the 9 alternative scores and each of the 3 dictionaries (Cambridge, EPA, Macmillan). ENV1 refers to the proportion of articles with at least one environmental term, ENV2 to the number of environmental words per article and ENV3 to the proportion of environmental words per article. The first panel (uniform weight) reports the results with uniform weights, the second (front-page weight) with a higher weight for environmental news on the front page, the last panel (title weight) with a higher weight for articles with an environmental word in the title.

Table 3: Signs and significance rates by sector

Sector	EPA & uniform weight				
	% signif	% (+)	% (+) signif	% (-)	% (-) signif
Communication Services	0.17	0.71	0.17	0.29	0.00
Consumer Discretionary	0.18	0.65	0.18	0.35	0.00
Consumer Staples	0.38	0.94	0.38	0.06	0.00
Energy	0.28	0.00	0.00	1.00	0.28
Financials	0.08	0.62	0.06	0.38	0.02
Health Care	0.15	0.61	0.13	0.39	0.02
Industrials	0.14	0.53	0.09	0.47	0.06
IT	0.09	0.54	0.07	0.46	0.01
Materials	0.28	0.16	0.04	0.84	0.24
Real Estate	0.84	1.00	0.84	0.00	0.00
Utilities	0.77	0.88	0.73	0.12	0.04
Sector	EPA & front-page weight				
	% signif	% (+)	% (+) signif	% (-)	% (-) signif
Communication Services	0.17	0.71	0.17	0.29	0.00
Consumer Discretionary	0.16	0.68	0.16	0.32	0.00
Consumer Staples	0.34	0.84	0.31	0.16	0.03
Energy	0.24	0.00	0.00	1.00	0.24
Financials	0.12	0.71	0.11	0.29	0.02
Health Care	0.11	0.63	0.10	0.37	0.02
Industrials	0.19	0.60	0.13	0.40	0.06
IT	0.10	0.57	0.09	0.43	0.01
Materials	0.36	0.20	0.04	0.80	0.32
Real Estate	0.77	1.00	0.77	0.00	0.00
Utilities	0.81	0.88	0.77	0.12	0.04

Notes: This table reports the percentages of significance for the environmental score by GICS sector, the percentages of + (-) coefficients and the percentages of + (-) significant coefficients. The results are given for the EPA dictionary and uniform weights (upper panel) or front-page weights (lower panel). For instance, 28% of coefficients are significant for materials and uniform weights, 4% being positive and 24% negative. 16% of coefficients are positive and 84% are negative.

Table 4a: Sectoral results

Firm	GICS Sub Industry	C.env	t.env	R2	Firm	GICS Sub Industry	C.env	t.env	R2
Consumer discretionary									
Foot Locker Inc	Apparel retail	1.63**	2.36	0.27	Leggett & Platt	Home Furnishings	0.10	0.19	0.52
Gap Inc.		-0.73	-0.89	0.23	Mohawk Industries		1.21	1.61	0.41
L Brands Inc.		0.66	0.64	0.26	Home Depot	Home Improvement Retail	0.79*	1.83	0.51
Ross Stores		0.58	0.97	0.33	Lowe's Cos.		0.94*	1.86	0.38
TJX Companies Inc.		0.88*	1.75	0.38	D. R. Horton	Homebuilding	1.20	1.63	0.30
Capri Holdings	Apparel, Accessories and Luxury Goods	-0.39	-0.37	0.12	Lennar Corp.		0.49	0.64	0.33
Hanesbrands Inc		1.24*	1.71	0.25	Pulte Homes Inc.		0.77	0.92	0.36
Nike		0.84	1.36	0.36	Carnival Corp.	Hotels, Resorts & Cruise Lines	1.26*	1.93	0.41
PVH Corp.		-0.88	-0.89	0.35	Hilton Worldwide Holdings Inc		-0.77	-1.06	0.42
Ralph Lauren Corp.		-0.28	-0.39	0.30	Marriott Int'l.		-0.21	-0.34	0.41
Tiffany & Co.		0.10	0.13	0.35	Royal Caribbean Cruises Ltd		1.40*	1.87	0.50
Tapestry, Inc.		-1.05	-1.57	0.33	Whirlpool Corp.	Household Appliances	-0.20	-0.30	0.38
Under Armour Class C		3.67	1.24	0.18	Amazon.com Inc.	Internet & Direct Marketing Retail	0.16	0.31	0.47
Under Armour Class A		2.55***	2.81	0.26	Booking Holdings Inc		-0.75	-1.01	0.36
V.F. Corp.		-0.03	-0.06	0.34	eBay Inc.		-0.75	-1.02	0.35
Aptiv Plc	Auto Parts & Equipment	0.26	0.44	0.43	Expedia Group		0.56	0.75	0.22
BorgWarner		0.67	0.91	0.48	Hasbro Inc.	Leisure Products	-1.08	-1.32	0.20
Ford Motor	Automobile Manufacturers	0.89*	1.75	0.46	Mattel Inc.		0.27	0.37	0.17
General Motors		0.93	1.59	0.42	Harley-Davidson	Motorcycle Manuf	1.31**	2.29	0.43
Advance Auto Parts	Automotive Retail	-0.27	-0.29	0.15	Chipotle Mexican Grill	Restaurants	0.82	0.74	0.14
MGM Resorts Intl.	Casinos & Gaming	0.61	0.64	0.40	Darden Restaurants		0.36	0.70	0.26
Wynn Resorts Ltd		-1.13	-1.10	0.31	McDonald's Corp.		-0.38	-1.18	0.33
Best Buy Co. Inc.	Computer & Electronics Retail	-1.20	-1.14	0.19	Starbucks Corp.		0.33	0.73	0.36
Garmin Ltd.	Consumer Electronics	0.04	0.06	0.27	Yum! Brands Inc		-0.73	-1.31	0.34
Nordstrom	Department Stores	0.51	0.64	0.31	Block H&R	Specialized Consumer Sv	-1.00	-0.84	0.15
Macy's Inc.		-1.04	-1.04	0.25	AutoZone Inc	Specialty Stores	0.42	0.80	0.15
LKQ Corp.	Distributors	0.15	0.30	0.42	Genuine Parts		-0.65	-1.57	0.51
Dollar General	General Merchandise Stores	1.10	1.54	0.19	Carmax Inc		0.81	1.29	0.37
Dollar Tree		1.22	1.53	0.17	O'Reilly Automotive		0.20	0.30	0.17
Kohl's Corp.		0.02	0.02	0.20	Tractor Supply Company		0.51	0.84	0.33
Target Corp.		0.04	0.07	0.24	Ulta Beauty		0.40	0.46	0.21
Consumer Staples									
Archer-Daniels-Midland Co	Agricultural Products	-0.64	-1.16	0.38	Hormel Foods Corp.	Packaged Foods & Meats	0.29	0.44	0.21
Molson Coors Brewing Company	Brewers	1.36**	2.15	0.28	The Hershey Company		1.44***	3.42	0.20
Brown-Forman Corp.	Distillers & Vintners	0.86**	2.12	0.36	Kellogg Co.		1.09***	3.00	0.20
Constellation Brands		1.44**	2.36	0.22	Kraft Heinz Co		-0.08	-0.08	0.22
Walgreens Boots Alliance	Drug Retail	0.82	0.99	0.35	Lamb Weston Holdings Inc		-3.11*	-1.72	0.10
Sysco Corp.	Food Distributors	0.81	1.36	0.34	Mondelez International		1.07**	2.06	0.38
Kroger Co.	Food Retail	0.93	1.32	0.16	McCormick & Co.		0.67*	1.81	0.28
Church & Dwight	Household Products	0.32	0.77	0.22	JM Smucker		0.72	1.25	0.23
Colgate-Palmolive		0.34	1.02	0.37	Tyson Foods		0.18	0.24	0.17
The Clorox Company		0.57	1.60	0.24	Coty, Inc	Personal Products	0.39	0.35	0.13
Kimberly-Clark		0.52	1.37	0.32	Estee Lauder Cos.		-0.11	-0.21	0.35
Costco Wholesale Corp.	Hypermarkets & Super Centers	0.35	0.89	0.38	Procter & Gamble		0.27	0.77	0.33
Walmart		0.72*	1.73	0.28	Coca-Cola Company	Soft Drinks	0.08	0.20	0.40
Conagra Brands	Packaged Foods & Meats	1.77***	4.19	0.21	Monster Beverage		0.88	1.09	0.17
Campbell Soup General Mills		0.59	1.30	0.13	Altria Group Inc	Tobacco	0.40	0.92	0.26
		0.68*	1.95	0.26	Philip Morris International		-0.13	-0.32	0.32

Table 4b: Sectoral results (continued)

Firm	GICS Sub Industry	C-env	t-env	R2	Firm	GICS Sub Industry	C-env	t-env	R2
Energy									
Chevron Corp.	Integrated Oil & Gas	-1.65***	-2.78	0.59	EOG Resources	Oil & Gas	-1.30	-1.01	0.40
Hess Corp.		-2.23*	-1.85	0.54	Diamondback Energy	Exploration & Production	-1.05	-0.46	0.28
Exxon Mobil Corp.		-0.67	-1.15	0.60	Marathon Oil Corp.		-2.28*	-1.80	0.40
Helmerich & Payne	Oil & Gas Drilling	-1.57	-1.14	0.42	Noble Energy Inc		-0.90	-0.64	0.36
BHGE	Oil & Gas Equipment & Services	-0.17	-0.13	0.32	Occidental Petroleum		-1.61**	-2.04	0.47
TechnipFMC		-2.27*	-1.72	0.42	Pioneer Natural Resources		-1.44	-0.88	0.41
Halliburton Co.		-1.54	-1.16	0.44	Cimarex Energy		-0.52	-0.38	0.38
National Oilwell Varco		-0.44	-0.46	0.46	HollyFrontier Corp	Oil & Gas Refining & Marketing	-0.29	-0.24	0.27
Schlumberger Ltd.		-0.84	-0.79	0.51	Marathon Petroleum		-0.86	-0.95	0.33
Apache Corp.	Oil & Gas Exploration & Production	-1.39	-1.10	0.44	Phillips 66		-1.86**	-2.55	0.36
Anadarko Petroleum Corp		-2.51**	-2.01	0.41	Valero Energy		-0.52	-0.77	0.41
Cabot Oil & Gas		-1.37	-1.55	0.23	Kinder Morgan		-0.91	-0.61	0.19
ConocoPhillips		-1.34	-1.62	0.45	ONEOK		-1.16	-1.21	0.29
Concho Resources		-2.32	-1.26	0.39	Williams Cos.		-1.23	-1.24	0.34
Devon Energy		-1.61	-1.48	0.42					
Industrials									
Arconic Inc.	Aerospace	0.87	0.43	0.37	Cintas Corporation	Diversified Support Sv	0.20	0.50	0.53
Boeing Company	& Defense	0.47	1.11	0.47	AMETEK Inc.	Electrical	0.55	1.24	0.63
General Dynamics		0.61*	1.69	0.56	Emerson Electric Company	Components	-0.71*	-1.89	0.59
Huntington Ingalls Industries		-0.63	-0.96	0.35	Eaton Corporation	& Equipment	-0.23	-0.54	0.63
Harris Corporation		-0.09	-0.17	0.45	Rockwell Automation Inc.		0.27	0.70	0.57
L-3 Communications Holdings		0.69	1.63	0.44	Rollins Inc.	Environmental & Facilities Services	0.57	1.54	0.51
Lockheed Martin Corp.		0.52	1.54	0.34	Republic Services Inc		0.54*	1.75	0.38
Northrop Grumman		0.54	1.55	0.47	Waste Management Inc.		-0.16	-0.42	0.41
Raytheon Co.		0.70*	1.81	0.37	Robert Half International	HR & Employment Sv	0.01	0.03	0.55
TransDigm Group		0.16	0.28	0.34	General Electric	Industrial Conglomerates	0.15	0.25	0.43
Tetxon Inc.		0.26	0.43	0.54	Honeywell Int'l Inc.		0.60*	1.92	0.73
United Technologies		0.03	0.10	0.64	3M Company		-0.20	-0.76	0.63
Deere & Co.	Agricultural Machinery	-0.78*	-1.87	0.45	Roper Technologies		0.49	1.39	0.59
C. H. Robinson Worldwide	Air Freight	0.15	0.29	0.29	Cummins Inc.	Industrial Machinery	-0.90	-1.51	0.56
Expeditors	& Logistics	0.90	1.55	0.45	Dover Corp.		-0.87	-1.32	0.60
FedEx Corp.		0.25	0.46	0.52	Flowers Corporation		-0.99	-0.89	0.57
United Parcel Service		0.09	0.25	0.55	Fortive Corp		-1.23	-1.33	0.49
American Airlines Group	Airlines	2.19	1.38	0.26	Grainger (W.W.) Inc.		0.25	0.41	0.35
Alaska Air Group Inc		1.99**	2.29	0.29	Ingersoll-Rand PLC		0.21	0.43	0.53
Delta Air Lines Inc.		1.07	1.06	0.20	Illinois Tool Works		-0.16	-0.40	0.63
Southwest Airlines		1.36	1.50	0.30	Parker-Hannifin		-0.06	-0.12	0.66
United Continental Holdings		1.81*	1.76	0.03	Pentair plc		-0.43	-0.71	0.55
Allegion	Building Products	1.13	1.63	0.44	Snap-on		0.39	0.97	0.59
A.O. Smith Corp		0.03	0.05	0.50	Stanley Black & Decker		-0.64	-1.18	0.49
Fastenal Co		0.21	0.42	0.43	Xylem Inc.		-0.12	-0.27	0.40
FBHS		0.38	0.56	0.39	CSX Corp.	Railroads	0.19	0.13	0.43
Johnson Controls Intl.		-0.11	-0.28	0.48	Kansas City Southern		-0.75	-1.21	0.45
Masco Corp.		0.31	0.56	0.47	Norfolk Southern Corp.		-0.83	-1.15	0.50
Fluor Corp.	Construction	-1.41	-1.54	0.58	Union Pacific		-0.74	-1.30	0.53
Jacobs Engineering Group	& Engineering	-0.91	-1.48	0.58	Equifax Inc.	Research & Consulting Services	1.18*	1.96	0.34
Quanta Services Inc.		-0.81	-0.89	0.38	IHS Markit Ltd.		0.86	0.83	0.28
Caterpillar Inc.	Construction Machinery & Heavy Trucks	-1.06*	-1.65	0.59	Nielsen Holdings		1.15*	1.83	0.24
PACCAR Inc.		-0.33	-0.77	0.63	Verisk Analytics		-0.08	-0.16	0.25
Wabtec Corp.		-1.27*	-1.91	0.49	United Rentals, Inc.	Trading & Distributors	1.94**	2.07	0.52
Copart Inc	Diversified Support Services	-0.18	-0.32	0.32	J. B. Hunt Transport Services	Trucking	0.73	1.28	0.43

Table 4c: Sectoral results (continued)

Firm	GICS Sub Industry	C_env	t_env	R2	Firm	GICS Sub Industry	C_env	t_env	R2
Materials									
Martin Marietta Materials	Construction Materials	-1.49	-1.63	0.34	PCA	Paper Packaging	0.02	0.03	0.43
Vulcan Materials		-0.56	-0.77	0.35	Sealed Air		-0.03	-0.06	0.37
Freeport-McMoRan Inc.	Copper	-4.13***	-3.46	0.39	WestRock		-0.57	-0.65	0.50
Eastman Chemical	Diversified Chemicals	-0.01	-0.02	0.58	Albemarle Corp	Specialty Chemicals	0.59	0.69	0.46
CF Industries Holdings Inc	Fertilizers &	-2.29**	-2.27	0.24	Celanese		-0.43	-0.71	0.54
EMC Corp.	Agricultural Chemicals	-0.77	-1.09	0.44	DowDuPont		-1.18*	-1.68	0.55
The Mosaic Company		-3.30***	-4.01	0.36	Ecolab Inc.		-0.38	-0.74	0.51
Newmont Goldcorp	Gold	-0.94	-0.86	0.04	Intl Flavors & Fragrances		0.79*	1.95	0.37
Air Products & Chemicals Inc	Industrial Gases	-0.77**	-2.07	0.52	LyondellBasell		-1.93*	-1.66	0.49
Linde plc		-0.82**	-2.47	0.53	PPG Industries		0.38	0.90	0.59
Ball Corp	Metal & Glass Containers	0.68	1.35	0.42	Sherwin-Williams		-0.30	-0.56	0.33
Avery Dennison Corp	Paper Packaging	-0.04	-0.07	0.42	Nucor Corp.	Steel	-0.97*	-1.83	0.55
International Paper		-0.50	-1.11	0.52					
Real Estate									
HCP Inc.	Health Care REITs	2.23***	3.61	0.18	UDR Inc	Residential REITs	1.52***	2.81	0.29
Ventas Inc		2.07***	3.24	0.19	Federal Realty	Retail REITs	1.12***	2.65	0.30
Welltower Inc.		2.09***	3.66	0.19	Kimco Realty		1.50***	3.06	0.36
Host Hotels & Resorts	Hotel & Resort REITs	0.62	1.06	0.54	Macerich		1.27*	1.80	0.33
Duke Realty Corp	Industrial REITs	1.32***	2.67	0.33	Realty Income Corp		1.20**	2.46	0.20
Prologis		1.56***	3.20	0.43	Simon Property		0.67*	1.78	0.33
Alexandria	Office REITs	1.44***	3.67	0.39	American Tower Corp.	Specialized REITs	0.68	1.50	0.31
Boston Properties		0.66*	1.70	0.39	Crown Castle Intl. Corp.		0.82	1.64	0.28
SL Green Realty		1.36**	2.51	0.46	Digital Realty Trust Inc		1.16*	1.86	0.18
Vornado Realty Trust		0.65	1.50	0.43	Equinix		0.80	1.52	0.24
CBRE Group	Real Estate Sv	0.72	1.44	0.53	Extra Space Storage		1.06*	1.69	0.26
Aimco	Residential REITs	1.35***	3.10	0.32	Iron Mountain		1.74**	2.24	0.24
AvalonBay Communities, Inc.		1.17***	2.61	0.27	Public Storage		1.04**	2.08	0.23
Equity Residential		1.08***	2.13	0.26	SBA Communications		0.59	1.08	0.27
Essex Property Trust, Inc.		1.27***	2.67	0.27	Weyerhaeuser		1.39**	2.53	0.50
Mid-America Apartments		1.66***	3.05	0.24					
Utilities									
American Electric Power	Electric Utilities	0.95**	2.26	0.22	AES Corp	Independent Power Producers	-0.74	-1.16	0.39
Dominion Energy		0.95**	2.01	0.23	NRG Energy	& Energy Traders	-2.41*	-1.91	0.17
Duke Energy		1.23***	3.24	0.19	Ameren Corp	Multi-Utilities	1.08**	2.23	0.20
Consolidated Edison		1.24***	3.04	0.20	CMS Energy	(Electricity & other)	1.24***	2.83	0.23
Edison Int'l		1.63***	2.83	0.18	CenterPoint Energy		-0.09	-0.18	0.28
Energy Corp.		0.72	1.53	0.19	DTE Energy Co.		0.96**	2.37	0.29
Energy		0.93*	1.78	0.19	Eversource Energy		1.01**	2.14	0.26
FirstEnergy Corp		0.93	1.49	0.19	Exelon Corp.		0.02	0.04	0.15
Public Serv. Enterprise Inc.		1.01*	1.95	0.23	NextEra Energy		0.65*	1.69	0.25
PPL Corp.		1.45***	2.41	0.18	NiSource Inc.		1.20**	2.49	0.24
Southern Co.		1.08***	2.66	0.18	Pinnacle West Capital		0.87**	1.82	0.23
Wec Energy Group Inc		1.00**	2.37	0.20	Sempra Energy		0.86*	1.91	0.27
Amos Energy Corp	Gas Utilities	1.28***	2.82	0.24	American Water Works Company Inc	Water Utilities	0.98**	2.10	0.23

Notes: This table reports, for each firm in consumer discretionary, consumer staples, energy, industrials, materials, real estate and utilities, the coefficient of the environmental score (column C_env), the t-statistic of this coefficient (column t_env) and the R-squared (column R2) in the Fama-French equation augmented with the environmental score. The results are given for the EPA dictionary and front-page weights. Significance levels: *** if the coefficient is significant at a 1%, ** at a 5%, * at a 10% level.

Table 5: Robustness tests (with EPA dictionary)

Variant	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Articles	all	all	all	all	all	all	all	all	US	epa
Weight	uniform	FP	FP	FP	FP	FP	FP	FP	FP	FP
Stocks	all	all	436	all	all	all	all	all	all	all
Time period	2010-19	2010-19	2010-19	2014-19	2010-19	2010-19	2010-19	2010-19	2010-19	bull bear
Specification	FF5	FF5	FF5	FF5	CAPM	FF3	FF5	FF5	FF5	FF5
HAC	5 lags	5 lags	5 lags	5 lags	5 lags	5 lags	1 lag	12 lags	5 lags	5 lags
7 sectors	0.34	0.35	0.36	0.27	0.35	0.37	0.34	0.36	0.30	0.27
Communication Svs	0.17	0.17	0.12	0.12	0.17	0.13	0.17	0.13	0.13	0.08
Consumer Discretionary	0.18	0.16	0.18	0.15	0.21	0.21	0.15	0.21	0.23	0.11
Consumer Staples	0.38	0.34	0.33	0.28	0.31	0.34	0.34	0.31	0.28	0.25
Energy	0.28	0.24	0.24	0.07	0.24	0.28	0.28	0.28	0.10	0.38
Financials	0.08	0.12	0.12	0.08	0.06	0.12	0.12	0.12	0.09	0.15
Health Care	0.15	0.11	0.12	0.08	0.11	0.11	0.13	0.11	0.06	0.16
Industrials	0.14	0.19	0.20	0.17	0.20	0.21	0.19	0.19	0.11	0.16
IT	0.09	0.10	0.11	0.15	0.10	0.10	0.09	0.10	0.10	0.09
Materials	0.28	0.36	0.35	0.20	0.28	0.36	0.40	0.32	0.28	0.24
Real Estate	0.84	0.77	0.77	0.61	0.81	0.81	0.68	0.84	0.97	0.58
Utilities	0.77	0.81	0.81	0.73	0.77	0.81	0.81	0.81	0.46	0.50

Notes: This table reports the percentage of significant environmental scores for the 275 firms in consumer discretionary, consumer staples, energy, industrials, materials, real estate and utilities and then per sector. Columns (1-2) report the benchmark results obtained with the EPA dictionary and uniform or front-page weights in the Fama-French five-factor equation (FF5). Column (3) contains the results for the 436 stocks available from 2010 to 2019. Column (4) reports the results for the 2014-2019 time period. Columns (5-6) report the results for the CAPM model and the Fama-French three-factor equation (FF3). Columns (7-8) contain the results for alternative AR orders (1 and 12) in the Newey West correction. Column (9) gives the results for articles related to the US only. Column (10) provides the percentage of significant environmental scores in bull and bear markets.

APPENDIX 1 - Environmental dictionaries based on Cambridge, Macmillan and EPA lexicons

Cambridge dictionary

acid precipitation, acid rain, anti consumerist, biodegrad, biological control, biome, bionomic, biotic, carbon captur, carbon credit, carbon emission, carbon footprint, carbon neutral, carbon offset, carbon sequestr, carbon sink, carbon tax, carbon trad, carbon zero, climate change, compost, conservancy, conservation, contamina, defiler, defolia, deforest, disafforest, disforest, eco, ecocide, ecocity, ecolog, ecosystem, ecotecture, ecotouris, ecotown, energy efficient, environment protect, environmental, food security, freecycle, fuel efficient, geoengineering, global warming, green audit, green bond, green energy, green fund, green power, green product, green purchas, green tech, greenhouse, greenness, greenwash, grey water, heliotherapy, hereditarianism, insolation, landfill, leachate, litter lout, litterbug, low energy, natural resource, nature protect, noise pollution, nox, nuclear fallout, nuclear waste, nuclear winter, off grid, off the grid, oil slick, oil spill, organophosphate, overpopulat, ozon, particulate, pcb, peak oil, pollut, preservationist, radioactive dust, reclaimab, recycl, refuse dump, remote sensing, renewab, reprocess, reusab, reuse, scrap yard, scrapyard, scrub, season creep, siriasis, slow city, smog, solar energy, solar power, sound pollution, spillage, sssi, sunstroke, sustainable development, thermic fever, tree hugger, unleaded, upcycl, water column, zero carbon, earth system governance project, esgp, global green growth institute, gggi, intergovernmental panel on climate change, ipcc, international union for conservation of nature, iucn, united nations environment program, unep, european environment agency, partnerships in environmental management for the seas of east asia, pemsea, environmental protection agency, epa, fish and wildlife service, national park service, inter tribal environmental council, greenpeace, center for environmental research and conservation, earth island institute, environmental defense fund, fauna and flora international, nature friends international, global footprint network, nature conservancy, natural resources defense council, nrdc, wetlands international, world agroforestry centre, worldwatch institute, world wildlife fund, wwf

EPA dictionary

nonradioactive, nontoxic, nss, ozon, reuse, smog, standing charge, weee, acid precipitation, acid rain, algae, algal, air pollution, air quality, alga, alternative energy sources, atomic number, atoxic, backyard burning, ber, bio fuel, biodegrad, biodiversity, bioenergy, biofuel, biomass, black bin, brown bin, bye law, carbon count, carbon credit, carbon dioxide, carbon emission, carbon footprint, carbon monoxide, carbon neutral, carbon offset, carbon tax, carbonic acid gas, carpooling, centennial state, cfc, cfl bulbs, chlorofluorocarbon, civic amenity site, climate change, co2, compost, conservation, cryptosporidium, deforest, dioxin, disforest, domestic charges, domestic waste, draught proofing, ecosystem, ecotouris, effluent, electric vehicle, emission allowance, emission projection, emission trad, emissions allowance, emissions projection, emissions trad, energy efficien, energy rating, energy star, environmental impact statement, flora and fauna, fossil fuel, fuel poverty, global warming, green bin, green design, greener homes scheme, greenhouse, grey bin, ground water, hazardous waste, home energy saving scheme, home ground, household waste, incinerator, kyoto agreement, kyoto protocol, kyoto treaty, landfill, mbt, modified organism, mulch, municipal waste, noise pollution, non poisonous, nonparticulate, nonpoisonous, noxious gases, npws, oil spill, organic, particulate, pay by weight, pesticide, planning permission, plastic bag, post consumer waste, radioactiv, radon, recycl, reforest, renewab, reprocess, river bassin, sewage, sewer water, smokeless fuel, solar array, solar battery, solar panel, sound pollution, surface water, sustainable development, sustainable touris, tidy town, toxic chemical, toxic emission, toxic fume, toxic landfill, toxic substance, toxic waste, traffic calming, un framework convention on climate change, ventilation, warmer homes scheme, waste management, waste prevention, wastewater, water vap, well water, wind energy, wind turbine, zero emission, earth system governance project, esgp, global green growth institute, gggi, intergovernmental panel on climate change, ipcc, international union for conservation of nature, iucn, united nations environment program, unep, european environment agency, partnerships in environmental management for the seas of east asia, pemsea, environmental protection agency, epa, fish and wildlife service, national park service, inter tribal environmental council, greenpeace, center for environmental research and conservation, earth island institute, environmental defense fund, fauna and flora international, nature friends international, global footprint network, nature conservancy, natural resources defense council, nrdc, wetlands international, world agroforestry centre, worldwatch institute, world wildlife fund, wwf

Macmillan dictionary

anthropogen, atoxic, biodegrad, biohazard, biological agent, biological control, bionomic, carbon captur, carbon cycle, carbon footprint, carbon neutral, carbon sink, carbon stor, carbon trad, catalytic converter, climate change, conservation, contamina, decarbonis, decarboniz, decarbur, decoke, deforest, disforest, dispersant, eco, ecocide, ecocity, ecolog, ecoterrorist, ecotouris, ecotown, emission trad, emissions trad, endangered species, environmental, feed in tariff, global warming, green audit, green belt, green bond, green energy, green fund, green power, green product, green purchas, green tech, greenhouse, greenly, greentailing, greenwash, nature reserve, nitrogen cycle, nonpoisonous, nontoxic, ozone friendly, pollut, rain forest, rainforest, re afforestation, reclaimab, recycl, reforest, renewab, reprocess, reusab, reuse, rewilding, sustainable development, toxic chemical, toxic emission, toxic fume, toxic landfill, toxic substance, toxic waste, u value, unleaded, water cycle, zero carbon, earth system governance project, esgp, global green growth institute, gggi, intergovernmental panel on climate change, ipcc, international union for conservation of nature, iucn, united nations environment program, unep, european environment agency, partnerships in environmental management for the seas of east asia, pemsea, environmental protection agency, epa, fish and wildlife service, national park service, intertribal environmental council, greenpeace, center for environmental research and conservation, earth island institute, environmental defense fund, fauna and flora international, nature friends international, global footprint network, nature conservancy, natural resources defense council, nrdc, wetlands international, world agroforestry centre, worldwatch institute, world wildlife fund, wwf

APPENDIX 2 - Estimation results (continued)

	C	MKT	SMB	HML	RMW	CMA	ECO	R2	DFS	C	MKT	SMB	HML	RMW	CMA	ECO	R2	ETFC	C	MKT	SMB	HML	RMW	CMA	ECO	R2
CINF	-0.1	0.8***	-0.1	0.2**	0.2*	0.6***	0.6**	0.52	DFS	0.0	1.1***	0.1	0.6***	0.0	-0.1	0.3	0.54	ETFC	0.0	1.4***	0.4***	1.4***	-0.9***	-1.4***	-0.2	0.57
CL	-0.2	0.7***	-0.3***	-0.5***	0.6***	0.8***	0.3	0.37	DG	-0.1	0.7***	0.4***	-0.3*	1.1***	0.3	1.1	0.19	FMC	-0.1	1.4***	0.3***	0.0	0.3*	0.9***	-0.2	0.63
CLX	-0.1	0.6***	-0.2**	-0.4***	0.6***	0.6**	0.6**	0.24	DGX	0.0	0.7***	-0.1	-0.1	0.1	-0.2	-0.4	0.25	FRC	-0.3	0.6***	-0.3***	-0.2*	0.4*	0.4*	0.7	0.19
CMA	0.1	1.1***	0.4***	1.9***	-0.1	-1.1***	-0.4	0.65	DHI	-0.3	1.1***	0.4*	0.1	-0.1	0.3	1.2	0.30	FRT	-0.2	0.5***	-0.2**	0.3*	0.5**	0.9*	0.19	
CMCSA	-0.1	1.0***	-0.2*	-0.1	0.2	0.4**	0.6	0.44	DHR	0.0	1.0***	-0.1	-0.2*	-0.2	0.1	0.1	0.63	FTI	0.0	0.9***	0.0	-1.2**	-0.1	0.5	0.6	0.22
CME	0.1	0.7***	0.0	0.7***	-0.3	-0.7***	-0.3	0.34	DIS	0.0	1.1***	-0.2**	0.0	0.0	0.4**	-0.2	0.55	FTNT	-0.2	0.5***	-0.4***	-0.1	0.4**	0.5**	0.0	0.15
CMG	0.0	0.7***	0.6***	-0.4	0.0	0.6	0.8	0.14	DISCA	-0.2	1.1***	0.3**	0.0	0.8***	0.4	0.2	0.31	FTV	-0.3*	1.1***	0.0	0.0	0.5**	0.4*	0.9	0.45
CMI	0.1	1.5***	0.4***	0.3*	0.4**	0.8***	-0.9	0.56	DISCK	-0.2	1.1***	0.2	-0.1	0.8***	0.6*	0.1	0.28	GD	-0.1	1.1***	-0.4**	-0.8**	0.0	0.5	0.6	0.22
CMS	-0.2	0.6***	-0.3***	-0.2	0.5***	0.6***	1.2***	0.23	DISH	-0.6*	1.2***	0.0	-0.2	0.1	0.7**	1.5*	0.33	GE	0.0	0.8***	0.0	-0.4*	0.0	0.7***	1.1*	0.26
CNC	0.3	0.9***	0.2	-0.5**	-0.6*	-0.1	-0.3	0.20	DLR	-0.2	0.7***	-0.2*	-0.5**	0.3	0.9***	1.2*	0.18	GILD	-0.5	1.2***	0.5***	0.3	0.3	0.5*	0.9*	0.46
CNP	0.0	0.7***	-0.3***	-0.2*	0.3*	0.6***	-0.1	0.28	DLTR	-0.1	0.7***	0.2	-0.2	1.1***	0.0	1.2	0.17	GIS	0.5	1.3***	0.0	0.3	-1.4***	1.2**	-1.0	0.28
COF	-0.2	1.2***	-0.1	1.1***	-0.4**	-0.7**	0.4	0.60	DOV	0.1	1.3***	0.3**	0.3**	0.2	0.7***	0.9	0.60	GLW	-0.1	1.1***	0.2*	0.3**	0.5**	0.5**	0.2	0.43
COG	0.3	0.9***	0.4**	0.3	-0.1	0.7**	-1.4	0.23	DRE	-0.4*	0.9***	-0.1	0.0	-0.1	0.4	1.3***	0.33	GM	-0.2	0.8***	-0.1	-0.4*	-1.1**	-1.5**	1.5*	0.20
COO	0.3	0.8***	0.1	-0.5**	0.0	0.0	0.89	0.28	DRI	0.0	0.8***	0.4***	-0.1	0.9***	0.3	0.4	0.26	GOOG	-0.1	1.2***	0.4**	-0.3*	0.3	0.8***	0.4	0.39
COP	0.2	1.0***	0.0	0.4**	-0.7**	0.7**	-1.3	0.45	DTE	-0.2	0.6***	-0.4***	-0.2*	0.5**	0.6**	1.0**	0.29	GOOGL	0.3	1.8***	0.7***	0.8**	0.2	1.2**	-4.1***	0.39
COST	0.0	0.8***	-0.1	0.0	0.6***	0.2	0.3	0.38	DUK	-0.1	0.4***	-0.4***	-0.09	0.15	0.6**	1.2**	0.19	GPC	-0.2	1.2***	0.2*	0.2*	0.4*	0.2	0.3	0.52
COTY	-0.5	0.9***	0.6	-0.5	1.3***	0.7	0.4	0.13	DVA	0.0	0.8***	0.0	-0.2	0.2	0.1	0.6	0.26	GPN	-0.4*	0.6**	-0.5**	-0.4**	0.4*	0.7***	0.9	0.19
CPB	-0.3	0.5***	-0.1	-0.3*	0.9***	0.6**	0.6	0.13	DVN	-0.1	1.2***	0.1	0.8***	-1.0**	0.2	-1.6	0.42	GPS	-0.2	1.1***	0.7***	-0.4*	-0.4	0.1	0.6	0.33
CPRI	0.0	0.9***	0.7**	0.4	1.0**	-0.3	-0.4	0.12	DWDP	0.1	1.4***	0.1	0.6***	0.2	0.0	-1.2*	0.55	GRMN	-0.1	0.9***	-0.2**	0.2*	0.1	0.2	0.8*	0.42
CPRT	0.2	0.8***	0.4***	-0.1	0.4**	-0.2	1.05	0.32	EA	0.2	1.0***	-0.1	-0.4*	-0.3	-0.5	-0.3	0.24	GS	0.0	0.9***	-0.1	0.1	0.1	-0.4	-0.1	0.30
CRM	0.0	1.2***	0.1	-0.5***	-0.6***	0.22	0.57	0.45	EBAY	0.1	1.1***	-0.1	-0.7***	0.0	-0.4	-0.8	0.35	GWV	-0.2	1.0**	0.2*	1.6**	-0.3	-0.9***	0.7	0.61
CSCO	-0.2	1.2***	-0.3***	0.0	0.1	-0.3	0.3	0.43	ECL	0.1	0.9***	-0.1	-0.1	0.2*	0.2	-0.4	0.51	HAL	-0.4	1.2***	0.8**	0.3	1.8***	-0.1	1.6**	0.27
CSX	0.3	1.2***	0.3**	0.4**	0.5	0.5	0.2	0.43	ED	-0.3	0.4***	-0.5***	-0.3***	0.5***	0.6***	1.2***	0.20	HAS	-0.1	0.9***	0.1	0.1	0.1	-0.4	-0.1	0.30
CTAS	0.1	1.0***	0.1	0.1	0.2*	0.0	0.2	0.53	EFX	0.1	1.0***	-0.1	-0.2	0.2	0.1	1.2**	0.34	HBAN	-0.1	1.6**	0.4**	0.6**	0.3	0.5*	-1.4	0.58
CTL	-0.4	1.0***	-0.2	-0.4**	0.4	0.9***	-0.6	0.22	EIX	0.0	0.6***	-0.3*	0.13	0.3*	0.4*	0.7***	0.18	HBI	-0.1	1.5***	0.4**	0.5***	0.4*	0.7***	-1.0	0.57
CTSH	-0.1	1.1***	0.0	-0.1	0.0	-0.3	0.1	0.41	EL	0.1	1.0***	0.1	-0.5**	0.4*	0.4*	-0.1	0.35	HCA	0.1	1.0***	0.1	0.0	0.0	-0.2	0.8	0.33
CTXS	0.1	1.2***	0.1	-0.2	-0.1	-0.4	-0.6	0.41	EMN	-0.1	1.3***	0.2*	0.3**	-0.1	0.1	1.2**	0.58	HCP	0.1	1.1***	0.2	0.0	-0.2	0.4	-0.8	0.44
CVS	-0.2	1.0***	-0.2	-0.2	0.5***	0.8***	0.3	0.34	EMR	0.0	1.2***	0.2**	0.0	0.3**	0.7**	-0.7**	0.59	HD	-0.1	0.8***	0.7***	1.1***	0.0	-1.0	1.2**	0.47
CVX	0.2	1.0***	-0.4***	0.3***	-0.3*	0.6***	-1.7***	0.59	EOG	0.2	1.1***	-0.1	0.3	-0.9***	0.6	-1.3	0.40	HES	-0.3**	0.7***	0.0	-0.4*	0.4*	0.6***	1.1***	0.30
CXO	0.4	1.3***	0.2	0.1	-1.0***	1.1**	-2.3	0.39	EQIX	-0.1	0.9***	-0.2	-0.4*	-0.4*	0.1	0.8	0.24	HFC	0.2	1.2***	0.1	0.4**	-0.9**	0.7*	-2.3*	0.42
D	-0.2	0.5***	-0.4***	-0.2	0.5***	0.5***	0.9*	0.23	EQR	-0.3	0.7***	-0.2*	-0.15	0.22	0.29	0.53	0.26	HIG	0.3	1.0***	0.4*	-0.5**	-0.8***	-0.9**	-0.2	0.27
DAL	-0.2	1.0***	0.3	0.3	0.4	-0.8*	1.1	0.20	ES	-0.2	0.6***	-0.3***	-0.3***	0.4**	0.7***	1.0**	0.26	HII	0.3	1.1***	-0.2*	0.0	0.3	0.1	-1.2	0.49
DE	0.1	1.1***	0.0	0.3**	0.0	0.5**	-0.8*	0.45	ESS	-0.3*	0.8***	-0.1	-0.2	0.2	0.3	1.3***	0.27	HLT	-0.2	1.1***	-0.2*	0.2*	0.2	0.3	0.6*	0.56
	-0.15	0.09	-0.12	0.14	0.20	0.23	0.42			-0.16	0.08	-0.12	0.14	0.20	0.21	0.47			-0.12	0.05	-0.10	0.12	0.13	0.20	0.36	

APPENDIX 2 - Estimation results (continued)

	C	MKT	SMB	HML	RMW	CMA	ECO	R2	HRS	C	MKT	SMB	HML	RMW	CMA	ECO	R2	K	C	MKT	SMB	HML	RMW	CMA	ECO	R2
GE	(-0.20)	1.1***	(-0.4*)	0.1	(-0.18)	(-0.6***)	0.1	0.43		0.0	1.0***	0.1	(-0.15)	(-0.2)	0.1	(-0.1)	0.45		(-0.4***)	0.5***	(-0.2)	(-0.11)	(-0.6***)	1.0***	0.20	
GILD	(0.1)	0.9***	(-0.15)	(-0.18)	(-0.7***)	(-0.30)	(0.59)	0.27	HSIC	(0.16)	(0.08)	(0.11)	(-0.15)	(-0.19)	(0.27)	(0.53)	0.40	KEY	(-0.12)	(0.04)	(0.09)	(-0.11)	(0.13)	(0.19)	(0.34)	0.65
GIS	(-0.3*)	0.6***	(-0.13)	(-0.17)	(-0.24)	(0.28)	(0.60)	0.26	HST	(-0.3*)	(0.05)	(0.09)	(0.12)	(0.17)	(0.22)	(0.47)	0.54	KEYS	(0.16)	(0.06)	(0.11)	(0.16)	(0.18)	(0.21)	(0.55)	0.43
GLW	(0.13)	0.07	(-0.3*)	(-0.2)	0.9***	0.5**	(0.35)	0.43	HSY	(-0.4**)	(0.08)	(0.11)	(0.15)	(0.22)	(0.23)	(0.58)	0.20	KHC	(0.31)	(0.14)	(0.19)	(0.22)	(0.28)	(0.48)	(1.35)	0.22
GM	(-0.16)	0.08	0.0	(-0.1)	0.1	(0.20)	(0.49)	0.42	HUM	(-0.3*)	(0.13)	(0.11)	(-0.3*)	(0.16)	(0.27)	(0.42)	0.21	KIM	(0.33)	(0.08)	(0.21)	(0.16)	(0.32)	(0.34)	(1.05)	0.36
GOOG	(-0.19)	0.08	(-0.13)	(-0.15)	(-0.22)	(0.26)	(0.58)	0.56	IBM	0.1	0.8***	0.2	0.1	0.1	(-0.5*)	(0.1)	0.21	KLAC	(-0.6***)	1.0***	0.1	(-0.3)	(0.3)	(0.9***)	(1.5***)	0.36
GOOGL	(0.16)	0.10	(-0.16)	(-0.14)	(-0.3)	(-0.39)	(0.57)	0.48	ICE	(-0.2)	0.9***	(-0.1)	0.0	(-0.3)	(0.26)	(0.57)	0.41	KLAC	(0.17)	(0.07)	(0.12)	(0.18)	(0.26)	(0.23)	(0.49)	0.43
GPC	(-0.17)	0.07	(-0.13)	(-0.12)	(-0.20)	(0.31)	(0.55)	0.51	IDXX	(0.14)	(0.06)	(0.11)	(0.11)	(0.14)	(0.21)	(0.50)	0.36	KMB	(0.31)	(0.08)	(0.14)	(0.18)	(0.22)	(0.29)	(1.26)	0.32
GPN	(0.13)	0.04	(-0.09)	(-0.11)	(-0.13)	(0.18)	(0.41)	0.44	IFF	0.2	0.9***	(-0.1)	(-0.1)	(0.22)	(0.29)	(0.57)	0.37	KMX	(-0.1)	(0.10)	(0.20)	(0.19)	(0.28)	(0.36)	(1.49)	0.19
GPS	(-0.2)	1.0***	0.1	(-0.5***)	0.1	(-0.1)	0.9**	0.61	INFO	(-0.2)	0.9***	(-0.1)	(-0.1)	0.2	0.4**	0.8**	0.28	KSS	(-0.3)	1.2***	0.5**	0.0	0.2	0.0	0.8	0.37
GRMN	(0.14)	0.06	(-0.11)	(-0.16)	(0.21)	(0.22)	(0.50)	0.23	ILMN	(0.16)	(0.06)	(0.16)	(0.17)	(0.17)	(0.18)	(0.40)	0.26	KO	(0.22)	(0.11)	(0.17)	(0.18)	(0.26)	(0.29)	(0.63)	0.40
GS	(-0.15)	0.07	(-0.14)	(-0.14)	(-0.19)	(0.23)	(0.49)	0.35	INTC	0.1	0.9***	0.2	(-1.1***)	(-1.3***)	(-0.6)	0.6	0.42	KSU	(-0.1)	0.7***	(-0.4***)	(-0.4***)	0.5**	0.8**	0.1	0.40
GWV	(0.28)	0.09	(-0.17)	(-0.21)	(-0.34)	(0.34)	(0.82)	0.27	INCY	(0.28)	(0.15)	(0.17)	(0.30)	(0.43)	(0.38)	(0.87)	0.24	KR	(0.10)	(0.05)	(0.07)	(0.09)	(0.11)	(0.12)	(0.40)	0.16
HAL	(-0.1)	1.5***	0.2	0.4**	(-0.4)	0.5	(-1.5)	0.44	INTU	(-0.1)	1.1***	0.3	(-1.3***)	(-1.6***)	(-0.1)	1.2	0.28	KSS	(-0.2)	0.7***	0.2	0.1	0.9**	0.4	0.9	0.16
HAS	(0.32)	0.10	(-0.19)	(-0.20)	(-0.26)	(0.38)	(1.33)	0.20	IP	(0.40)	(0.15)	(0.32)	(0.37)	(0.40)	(0.52)	(1.08)	0.52	LB	(0.24)	(0.08)	(0.17)	(0.18)	(0.22)	(0.28)	(0.71)	0.20
HBAN	(-0.2)	0.7***	0.3**	(-0.1)	0.5**	0.0	(-1.1)	0.20	IPG	(-0.1)	1.3***	0.2	0.0	0.4**	0.8**	(-0.5)	0.40	LH	(-0.4)	1.1***	0.5**	(-0.2)	1.2***	0.8**	0.7	0.26
HCP	(0.22)	0.07	(-0.14)	(-0.15)	(-0.21)	(0.27)	(0.82)	0.60	IR	(0.15)	(0.07)	(0.12)	(0.15)	(0.17)	(0.24)	(0.45)	0.47	LEG	(0.31)	(0.13)	(0.19)	(0.20)	(0.34)	(0.34)	(1.03)	0.52
HBI	(-0.15)	0.07	(-0.13)	(-0.18)	(-0.19)	(0.22)	(0.53)	0.25	IRGP	(-0.2)	1.4***	0.1	(-0.3*)	0.2	0.6**	0.3	0.27	LEN	(-0.2)	1.1***	0.4**	0.0	0.7**	0.6**	0.1	0.52
HCA	(0.27)	0.10	(-0.16)	(-0.19)	(-0.34)	(0.39)	(0.73)	0.20	IQV	0.4	1.3***	0.5*	(-0.5)	(-0.8*)	(-0.2)	(-0.48)	0.24	LKQ	(0.14)	(0.07)	(0.11)	(0.13)	(0.17)	(0.20)	(0.55)	0.33
HCP	(-0.2)	1.0***	(-0.1)	(-0.3)	(-0.1)	0.3	(-1.1)	0.54	ISRG	(0.34)	(0.11)	(0.27)	(0.31)	(0.42)	(0.46)	(0.88)	0.24	LLK	(0.21)	(0.11)	(0.21)	(0.26)	(0.29)	(0.35)	(0.76)	0.44
HFC	(0.31)	0.09	(-0.17)	(-0.19)	(-0.26)	(0.36)	(1.20)	0.27	IT	(0.17)	(0.09)	(0.15)	(0.13)	(0.22)	(0.25)	(0.50)	0.37	LLY	(0.15)	(0.06)	(0.12)	(0.12)	(0.17)	(0.20)	(0.42)	0.74
HIG	(-0.36)	0.12	(-0.19)	(-0.25)	(-0.32)	(0.38)	(1.18)	0.61	ITW	(-0.17)	(0.08)	(0.12)	(0.13)	(0.18)	(0.23)	(0.49)	0.43	LOW	(-0.1)	0.9***	0.0	0.0	0.3**	0.4**	0.7	0.38
HII	(-0.3)	1.3***	(-0.2)	0.7***	(-0.4)	0.1	0.8**	0.27	JEB	0.0	1.1***	0.2**	0.2**	0.4**	0.0	(-0.2)	0.63	LMT	(0.16)	(0.06)	(0.13)	(0.13)	(0.18)	(0.20)	(0.60)	0.34
HIT	(0.16)	0.09	(-0.10)	(-0.13)	(-0.17)	(0.21)	(0.43)	0.43	JCI	(0.13)	(0.05)	(0.08)	(0.09)	(0.14)	(0.16)	(0.39)	0.48	LRCX	(0.12)	(0.06)	(0.11)	(0.13)	(0.14)	(0.21)	(0.34)	0.44
HIX	(-0.3)	1.1***	0.3*	0.1	(-0.3)	0.4	(-0.6)	0.35	IVZ	(-0.4*)	1.5***	0.2*	0.8**	(-0.1)	(-0.5**)	(-0.1)	0.68	LNC	(-0.1)	1.6**	0.2*	1.7***	(-0.9***)	0.0	0.74	
HJ	(0.20)	0.10	(-0.17)	(-0.17)	(-0.20)	(0.27)	(0.66)	0.42	JBHT	(0.17)	(0.07)	(0.11)	(0.16)	(0.15)	(0.21)	(0.46)	0.37	LNU	(0.16)	(0.06)	(0.11)	(0.14)	(0.19)	(0.20)	(0.47)	0.38
HON	(-0.2)	1.2***	(-0.1)	0.0	0.2	0.4**	0.6*	0.73	JEF	(-0.2)	0.9***	0.4***	0.3**	0.5**	0.1	0.7	0.43	LW	(-0.2)	1.0***	0.2*	0.0	0.7***	0.5*	0.9*	0.38
HOG	(-0.09)	0.04	(-0.07)	(-0.09)	(-0.12)	(0.14)	(0.31)	0.42	JKHY	(0.16)	(0.05)	(0.12)	(0.15)	(0.19)	(0.20)	(0.46)	0.59	LYB	(0.18)	(0.06)	(0.11)	(0.14)	(0.21)	(0.30)	(0.51)	0.10
HOLX	(-0.18)	0.10	(-0.15)	(-0.20)	(-0.27)	(0.35)	(0.57)	0.27	JNJ	0.1	0.9***	0.2**	(-0.3**)	0.2*	0.0	(0.46)	0.49	LYB	(0.36)	(0.13)	(0.37)	(0.38)	(0.42)	(0.59)	(1.81)	0.49
HPE	(-0.3)	0.9**	0.1	(-0.3*)	(-0.1)	0.0	1.2**	0.43	JNPR	(0.14)	(0.06)	(0.09)	(0.15)	(0.19)	(0.25)	(0.40)	0.41	M	(0.21)	(0.08)	(0.14)	(0.20)	(0.25)	(0.30)	(0.73)	0.30
HPE	(-0.2)	1.5***	0.2	0.2	(-0.1)	0.3	1.0	0.43	JNPR	0.0	0.7***	(-0.4***)	(-0.2)	0.0	0.3*	0.0	0.41	MA	(0.26)	(0.08)	(0.16)	(0.19)	(0.22)	(0.26)	(1.16)	0.25
HPQ	(-0.5)	1.3***	0.2	(-0.1)	0.5*	0.2	(0.45)	0.34	JNPR	(0.09)	(0.05)	(0.06)	(0.11)	(0.10)	(0.16)	(0.31)	0.33	MA	(0.29)	(0.10)	(0.19)	(0.20)	(0.38)	(0.40)	(1.01)	0.46
HRB	(-0.26)	0.09	(-0.15)	(-0.17)	(-0.27)	(0.35)	(0.77)	0.15	JPM	(-0.23)	(0.11)	(0.18)	(0.21)	(0.27)	(0.31)	(0.70)	0.73	MAA	(0.15)	(0.07)	(0.13)	(0.12)	(0.19)	(0.21)	(0.45)	0.24
HRL	(-0.32)	0.09	(-0.2)	(-0.3)	(-0.1)	0.2	(-1.0)	0.21	JWN	0.0	1.1***	(-0.4***)	(-0.4***)	(-0.8***)	(-0.9***)	(-0.2)	0.31	MAC	(-0.4***)	0.7***	(-0.1)	(-0.3**)	0.4*	0.5**	1.7***	0.24
	(0.1)	0.6***	(-0.2)	(-0.5***)	0.5**	0.9**	0.3	0.21	JWN	(0.13)	(0.05)	(0.12)	(0.09)	(0.14)	(0.16)	(0.40)	0.31	MAC	(0.16)	(0.06)	(0.11)	(0.15)	(0.21)	(0.24)	(0.54)	0.33
	(0.18)	0.06	(0.11)	(0.13)	(0.16)	(0.22)	(0.67)	0.21	JWN	(-0.4)	1.2***	0.6**	0.2	1.2**	0.2	0.5	0.31	MAC	(-0.5**)	1.0***	(-0.1)	(-0.3)	0.3	0.9**	1.3*	0.33

APPENDIX 2 - Estimation results (continued)

	C	MKT	SMB	HML	RMW	CMA	ECO	R2	C	MKT	SMB	HML	RMW	CMA	ECO	R2	C	MKT	SMB	HML	RMW	CMA	ECO	R2
MAR	0.2	1.0***	0.4**	-0.3	0.8***	0.3	-0.2	0.41	-0.1	0.6***	-0.5***	-0.3***	0.3*	0.4**	0.7*	0.25	0.1	1.2***	0.0	-0.4***	-0.2	0.0	-0.5	0.52
MAS	-0.2	1.4***	0.3**	0.2	-0.1	0.6**	0.3	0.47	0.0	0.4***	0.1	-0.2	0.2	1.1**	-0.9	0.04	-0.4	1.1***	-0.1	-0.1	-0.2	0.6**	1.6***	0.43
MAT	-0.4	0.9***	0.5**	-0.5**	0.7*	0.7*	0.3	0.17	0.2	1.1***	0.1	-0.2	-0.5	-1.7***	1.4	0.14	-0.1	0.9**	-0.5***	-0.4***	0.5***	0.6***	-0.1	0.32
MCD	0.26	0.11	0.20	0.24	0.36	0.41	0.74	0.33	0.43	0.18	0.42	0.30	0.58	0.56	1.21	0.24	-0.1	1.0***	0.1	1.3***	-0.4	-0.7	0.5	0.69
MCHP	-0.1	0.7***	0.08	0.08	0.12	0.16	0.32	0.46	0.14	0.06	0.10	0.11	0.19	0.6	0.8	0.36	-0.1	1.3***	0.3**	0.2	0.4**	0.8***	-0.4	0.55
MCK	-0.3	0.8***	0.1	-0.4**	-0.2	0.3	0.8	0.28	0.16	0.07	0.11	0.17	0.17	0.24	0.61	0.21	-0.2	0.6***	-0.2**	-0.2**	0.5***	0.6***	0.9*	0.23
MCO	0.0	1.2***	-0.3	0.0	-0.6***	-0.6**	0.2	0.47	-0.5**	0.9***	0.1	-0.4	0.1	0.7***	1.2*	0.24	-0.1	1.2***	0.2*	0.0	0.3*	0.6***	0.4	0.59
MDLZ	-0.3	1.0***	-0.5***	-0.6***	0.3	0.8***	1.1**	0.38	0.0	1.0***	-0.1	-0.1	0.2	0.5*	0.5	0.47	-0.5	0.5***	-0.4***	0.3*	1.5***	1.0**	0.18	
MDT	-0.1	0.9***	-0.4**	-0.2*	0.0	0.0	0.2	0.45	-0.3	1.3***	0.3*	0.3*	0.15	0.21	0.35	0.46	-0.9	1.2***	0.2	-1.0***	-0.5	0.5	1.5	0.25
MET	-0.3	1.3***	0.1	1.3***	-0.7***	-0.8***	0.3	0.71	0.4	0.9***	0.0	-0.4	-0.4	0.7	-2.4*	0.17	-0.3	1.4***	0.0	1.3***	-0.4***	-0.8***	0.7	0.75
MGM	-0.3	1.4***	0.5**	0.0	-0.8**	-0.1	0.6	0.40	0.2	1.2***	0.0	0.4***	0.3	0.2	-0.8	0.50	-0.2	0.7***	-0.2**	-0.3*	0.0	0.5**	1.0**	0.23
MHK	-0.4	1.2***	0.5***	0.0	0.4*	0.4	1.2	0.41	0.0	1.2***	0.3**	-0.2	-0.3	0.0	-0.9	0.37	0.4*	1.1***	-0.2	0.5***	-0.5**	-0.3	-1.9***	0.36
MKC	-0.1	0.7***	-0.2	-0.4***	0.7***	0.2	0.7	0.28	0.0	1.0***	0.0	1.1***	0.24	0.30	0.3	0.61	0.1	1.3***	0.7***	-0.1	0.8***	0.2	-0.9	0.35
MLM	0.3	1.0***	0.5***	0.2	0.1	0.3	-1.5*	0.34	0.0	1.3***	0.3*	0.5***	0.3*	0.4*	-1.0*	0.55	0.1	1.1***	0.6***	0.4*	0.5***	0.4	-0.1	0.38
MMC	0.0	0.8***	-0.1	0.0	-0.1	0.3*	0.3	0.55	0.2	1.4***	0.2	-0.5**	-0.7*	0.6	-0.4	0.35	0.3	1.3***	0.1	0.4*	0.8***	0.7*	-1.4	0.41
MMM	-0.1	1.1***	-0.2	0.0	0.5**	0.2	-0.2	0.63	0.3	1.1***	0.0	0.0	0.3	1.2***	0.6	0.38	0.0	1.2***	-0.4**	-0.5**	0.2	1.3	0.45	
MNST	0.0	0.9***	-0.2	-0.8***	0.3	0.6*	0.9	0.17	0.25	1.2***	-0.2	0.0	0.4	0.5	0.5	0.38	-0.1	1.1***	-0.2	-0.6***	0.1	0.0	-0.5	0.35
MO	-0.1	0.7***	-0.4**	-0.3*	0.7***	0.6**	0.4	0.26	-0.3	0.6**	0.0	-0.6***	0.5**	0.9**	1.2**	0.20	-0.4	0.8***	0.8**	0.3	-0.4	-2.4***	0.4	0.24
MOS	0.3	1.2***	0.3*	0.3	-0.5*	0.6*	-3.3***	0.36	0.3	1.1***	0.0	0.0	-0.3	1.2***	-1.2	0.29	-0.4	1.6***	0.3*	-0.2	0.5*	0.1	1.4*	0.50
MPC	0.2	1.2***	-0.1	1.7***	-1.0*	-0.9*	-0.9	0.33	-0.2	1.1***	0.0	-0.2	0.2	0.6***	0.2	0.53	0.0	0.5***	0.0	0.4***	0.1	-0.4	0.3	0.25
MRK	0.2	0.8***	-0.4**	-0.4**	-0.2	0.5*	-0.8*	0.34	0.14	1.1***	0.06	0.10	0.16	0.22	0.41	0.47	0.4	1.0***	0.1	-1.5***	-0.9**	0.2	-0.4	0.26
MRO	0.3	1.3***	0.1	0.7***	-1.4	0.4	-2.3*	0.40	0.2	0.7***	0.0	-0.2	0.8***	0.1	0.2	0.17	0.33	1.2***	0.3*	2.0***	-1.1***	0.2	0.66	
MS	-0.1	1.3***	-0.1	1.7***	-1.0*	-0.9*	-0.9	0.69	0.1	1.1***	-0.1	0.2	-0.6***	0.6***	-1.6**	0.47	0.0	1.3***	0.4**	0.3**	0.0	-0.2	0.0	0.55
MSCI	0.1	1.0***	0.2	-0.1	-0.1	-0.6*	0.2	0.40	0.0	0.9**	-0.1	-0.1	0.4**	0.2	-0.2	0.55	-0.1	1.2***	0.4**	-0.7***	-0.2	-0.4	0.5	0.36
MSFT	0.0	1.1***	-0.4**	0.0	0.6***	-0.8*	0.0	0.49	-0.2	0.8***	0.3**	1.0***	0.0	-0.7***	0.0	0.58	0.2	1.2***	0.3**	0.8***	-0.4**	-0.5**	-0.9*	0.62
MSI	-0.1	0.9***	0.0	-0.2	0.0	0.1	0.6	0.34	0.11	1.3***	0.4**	0.5***	0.3*	0.4*	-0.3	0.63	-0.1	1.1***	0.6***	0.1	0.7***	-0.5	-0.3	0.30
MTB	-0.1	0.9***	0.1	1.3***	-0.1	-0.8***	0.3	0.59	-0.3	0.7**	-0.4	-0.3	0.5**	0.6**	1.0*	0.23	0.0	0.8**	-0.1	-0.5**	0.0	0.2	0.2	0.20
MTD	0.1	1.2***	0.0	-0.5***	-0.1	0.2	-0.3	0.54	0.1	0.8***	-0.4	-0.5***	-0.3**	0.7***	-0.6	0.40	-0.1	1.3***	0.2*	0.1	0.0	0.4**	0.3	0.57
MU	0.1	1.5***	0.3	0.2	-1.1***	-0.9**	-0.8	0.33	-0.1	0.6***	-0.4	-0.3	0.5***	0.7***	0.3	0.33	0.0	0.9**	0.4**	-0.1	0.3*	0.2	0.6	0.51
MXIM	0.1	1.1***	0.1	-0.4***	-0.2	-0.1	-0.7	0.42	0.0	0.8**	-0.2	0.2**	0.2	-0.1	0.3	0.40	0.0	1.0**	0.1	-0.1	0.0	0.3*	0.5	0.59
MYL	-0.6**	1.1***	-0.1	-0.8***	-0.6*	0.4	1.8*	0.29	-0.1	1.4***	0.2*	0.2	0.2	0.6***	-0.1	0.66	0.0	1.0**	0.2	-0.2	1.0***	0.3	0.6	0.33
NBL	-0.1	1.2***	-0.1	0.2	-0.8***	0.9**	-0.9	0.36	-0.3	1.3***	0.5**	0.5**	-0.1	0.1	0.8	0.36	-0.1	0.7**	-0.1	0.0	0.5***	0.3	0.5	0.38
NDAQ	-0.1	1.1***	0.06	0.22	0.20	0.39	1.40	0.47	0.0	1.1***	0.2*	-0.2	0.0	0.5*	0.0	0.43	-0.1	0.9**	-0.2*	-0.1	0.2	0.4*	0.7*	0.37
	0.16	1.0**	0.10	0.14	0.16	0.21	0.48	0.19	0.19	0.07	0.11	0.18	0.20	0.26	0.56	0.20	0.13	0.06	0.12	0.13	0.18	0.21	0.39	0.37

APPENDIX 2 - Estimation results (continued)

	C	MKT	SMB	HML	RMW	CMA	ECO	R2	C	MKT	SMB	HML	RMW	CMA	ECO	R2	C	MKT	SMB	HML	RMW	CMA	ECO	R2
SBAC	0.0	0.8***	-0.2	-0.5***	0.1	0.6***	0.6	0.27	0.0	0.9***	0.1	0.6***	0.0	0.0	0.5**	0.71	0.1	0.6***	0.2*	0.1	0.4**	0.2	-0.1	0.25
SBUX	0.0	0.9***	0.1	-0.2*	0.8***	-0.1	0.3	0.36	0.0	1.0***	-0.2*	-0.5***	-0.3*	0.1	0.3	0.55	0.0	0.9***	0.0	-0.1	0.1	0.0	0.7	0.35
SCHW	0.1	1.2***	0.1	1.4***	-0.7***	-1.4***	-0.5	0.61	-0.1	1.2***	0.6***	0.0	0.8***	0.4	-1.0	0.33	-0.2	1.0***	-0.1	-1.3***	-1.4**	0.1	1.1	0.18
SEE	-0.1	1.1***	0.1	-0.1	0.4**	0.3	0.0	0.37	-0.5	1.3***	-0.3	-1.1***	-1.2*	0.5	1.3	0.20	-0.6***	0.7***	-0.2	-0.5	0.3	0.9***	2.1***	0.19
SHW	0.2	0.8***	0.1	-0.2	0.3*	0.2	-0.3	0.33	0.42	1.3***	-0.1	0.4***	-0.2*	0.0	0.2	0.73	0.21	0.7***	-0.2*	0.1	0.6***	0.2	0.2	0.31
SIVB	0.1	1.3***	0.8***	1.9***	-0.3	-1.9***	-0.1	0.64	0.12	0.8***	-0.4**	0.0	0.4***	0.6***	0.6**	0.47	0.3	1.2***	0.4***	0.1	0.1	0.6**	-1.3*	0.49
SJM	-0.3	0.7***	-0.2	-0.3*	0.7***	0.6***	0.7	0.23	0.0	1.2***	0.4***	-0.3*	0.8***	0.8***	0.5	0.33	0.1	1.0***	0.0	-0.4***	-0.3*	-0.1	-0.4	0.48
SLB	-0.1	1.2***	0.0	0.5***	-0.7*	0.4	-0.8	0.51	0.1	0.8***	-0.1	0.0	0.6**	0.4	0.2	0.17	-0.5*	1.1***	-0.1	-0.5	0.2	1.1***	0.8	0.35
SLG	-0.5	1.1***	0.2**	-0.1	0.1	0.3	1.4***	0.46	0.1	1.0***	-0.2*	-0.4**	0.0	0.0	-0.1	0.47	0.4	1.0***	0.4**	-0.4*	0.2	0.2	-1.0	0.20
SNA	-0.1	1.1***	0.4***	0.3*	0.3*	0.1	0.4	0.59	0.3	0.9***	0.3	-0.3	-0.7*	-0.5	-0.3	0.29	0.30	1.3***	0.2	0.3	-0.6*	-0.4	-0.4	0.25
SNPS	0.2	0.9***	0.1	-0.3**	-0.1	-0.2	-0.4	0.53	0.1	0.9***	1.2***	-0.9*	-0.2	-1.4	-2.0	0.19	-0.2	0.5***	-0.3*	-0.3**	0.6***	0.5***	1.0**	0.20
SO	-0.3	0.4***	-0.3***	-0.2*	0.5**	0.4**	1.1***	0.18	0.0	1.2***	0.0	0.0	0.0	-0.2	0.0	0.50	-0.6***	0.6***	-0.2*	-0.6**	0.2	0.8***	2.1***	0.19
SPG	-0.2	0.8***	0.0	-0.3*	0.4**	0.8***	0.7	0.33	0.15	1.5***	0.07	0.0	-0.1	0.8***	0.3	0.54	0.19	1.0***	-0.1	1.1***	-0.3*	-0.5***	0.3	0.66
SPGI	0.2	1.0***	-0.2	0.0	-0.2	-0.1	-0.3	0.36	-1.5**	1.4***	1.2**	-0.1	0.7	0.6	3.7	0.18	-0.2	1.3***	0.6**	-0.2	0.7***	1.2***	-0.2	0.38
SRE	-0.2	0.7***	-0.5***	-0.1	0.1	0.3	0.9**	0.27	0.6*	1.3***	0.8***	0.0	0.1	-0.3	2.5**	0.26	-0.3	1.0***	-0.2*	0.1	-0.3	0.2	1.8	0.45
STI	-0.1	1.2***	0.2*	1.7***	-0.5**	-0.9***	0.6	0.67	0.33	1.3	0.13	0.27	0.44	0.35	0.61	0.03	0.24	1.0***	0.11	0.18	0.24	0.29	1.10	0.41
STZ	-0.1	0.9***	0.0	-0.5**	0.2	0.8***	1.4**	0.22	0.2	1.0***	0.8***	-0.1	0.8***	-0.1	0.4	0.21	-0.3	1.5***	0.4**	0.3	0.4	0.0	-0.6	0.50
STT	-0.2	1.2***	0.1	0.8***	-0.6**	-0.2	0.0	0.58	-0.4***	0.8***	-0.1	-0.2	0.4**	0.5*	1.5***	0.29	0.1	1.3***	0.3*	0.2	-0.7**	0.2	-1.2	0.34
STX	-0.1	1.4***	0.5**	0.1	0.6	-0.3	-0.2	0.25	0.15	0.9***	0.1	-0.1	-0.3	0.1	0.8	0.27	-0.2	0.7***	-0.3*	-0.1	0.9***	0.6**	0.7*	0.28
STZ	-0.1	0.9***	0.0	-0.5**	0.2	0.8***	1.4**	0.22	0.2	1.0***	0.8***	-0.1	0.8***	-0.1	0.4	0.21	-0.3	1.5***	0.4**	0.3	0.4	0.0	-0.6	0.50
SWK	0.1	1.2***	0.2*	0.2	0.4**	0.0	-0.6	0.49	0.17	0.9***	-0.3*	-0.1	0.1	0.1	1.0*	0.37	-0.2	0.9***	0.1	0.1	-0.2	0.0	-0.1	0.33
SWKS	-0.2	1.4***	0.4*	-0.3	-0.4	-1.4***	1.0	0.36	0.17	1.1***	0.1	1.1***	-0.3	0.5**	0.55	0.60	-0.6***	1.2***	0.2	0.0	0.2	0.4*	1.4**	0.50
SYF	-0.2	1.1***	0.3	1.1***	-0.1	-1.1***	1.2	0.41	0.2	1.1***	0.1	0.2*	0.3*	0.5**	-0.7	0.53	0.0	1.4***	0.4	-0.6**	-0.1	-0.1	-1.1	0.31
SYK	-0.2	0.9***	-0.2	-0.1	0.0	-0.1	0.8*	0.48	0.15	1.0***	0.0	0.2*	0.6***	0.4*	0.1	0.55	-0.1	1.3***	0.1	0.4**	-0.7**	0.9***	-0.5	0.38
SYMC	-0.3	1.1***	-0.1	-0.6***	0.3	0.8**	0.1	0.24	0.12	1.0***	1.0***	0.4	0.1	0.4	1.9**	0.52	0.0	1.0***	0.2	-0.4***	-0.5***	0.1	0.5	0.40
SYZ	-0.2	0.7***	0.1	-0.1	0.7***	0.4**	0.8	0.34	0.0	1.0***	-0.1	0.8***	-0.3*	-0.4***	-0.1	0.67	0.0	1.0***	-0.4***	0.0	-0.3**	0.8***	-0.7	0.60
T	-0.2	0.7***	-0.2	-0.1	0.0	0.4**	0.2	0.35	-0.2*	1.1***	0.1	0.0	0.3**	0.5**	0.0	0.64	-0.3*	1.0***	0.0	-0.1	0.2	0.1	0.5	0.40
TAP	-0.5	0.9***	-0.3*	-0.5***	0.1	0.9***	1.4**	0.28	0.3**	1.0***	-0.2*	-0.3**	-0.1	-0.1	-0.5	0.45	-0.5**	1.4***	0.1	-0.1	-0.1	0.5*	0.9	0.46
TDG	0.2	0.9***	0.1	-0.1	0.0	-0.2	0.2	0.34	0.13	0.9***	0.1	-0.4***	-0.2	0.2	0.6	0.38	0.0	1.1***	0.0	0.1	0.3	0.4	-0.1	0.40
TEL	0.0	1.2***	0.2**	0.0	-0.1	-0.2	-0.2	0.58	0.1	0.9***	0.2*	0.1	0.6***	-0.4	0.0	0.34	0.2	0.9***	-0.3*	-0.3**	0.3	0.2	-0.7	0.34
TFX	-0.1	0.9***	0.1	-0.4**	0.0	0.3	1.0*	0.38	-0.4	1.2***	0.3	-0.2	0.0	1.3**	-0.2	0.25	-0.1	0.9***	-0.1	-0.2	0.1	0.1	0.1	0.32
TGT	-0.1	0.8***	0.2	-0.1	0.8***	0.5**	0.0	0.24	0.31	1.1***	0.11	0.21	0.34	0.43	1.13	0.41	0.18	1.0***	0.07	0.16	0.22	0.24	0.53	0.64
TIF	-0.1	1.1***	0.6***	0.0	0.7***	0.0	0.1	0.35	0.23	1.1***	0.15	0.19	0.24	0.34	0.67	0.35	0.17	0.8***	0.14	0.15	0.21	0.26	0.47	0.40
TJX	-0.1	0.9***	0.2*	0.17	0.21	0.22	0.33	0.38	0.24	1.0***	0.09	0.15	0.20	0.23	0.72	0.43	0.15	0.9***	0.11	0.14	0.19	0.23	0.44	0.40

Notes: This table reports, for each firm, the parameter estimations, the associated standard errors in brackets and the R-squared in the Fama-French equation augmented with the environmental score. Significance levels: *** if the coefficient is significant at a 1%, ** at a 5%, * at a 10% level.