A green wave in media, a change of tack in stock markets

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Abstract

This paper explores the impact of green sentiment in US media on financial markets. Using textual analysis with a dictionary-based approach, we retrieve several scores of attention, tonality and uncertainty in the coverage of environmental news of four major US newspapers. We consider various weighting schemes to account for the visibility and relevance of the text sources and several sets of newspapers to measure the possible impact of their editorial line. Our results establish that greater attention to environmental news in US media reduced the excess returns of carbon-intensive stocks and increased their volatility over the last decade, especially when the coverage was negative or uncertain. The opposite result holds for the most virtuous green assets. Restricting the corpus of texts to conservative newspapers mitigates the impact of the coverage. Overall, our findings illustrate how rising environmental concerns lead investors to shift their asset allocation.

JEL Classification: G12, G14, Q53, Q54.

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

1 Introduction

In May 2021, ExxonMobil's shareholders voted to replace three board members with directors better suited to taking action on climate change. The shake-up was led by an activist hedge fund and supported overwhelmingly by much larger institutional investors. Naturally, this rebellion on the board of one of the world's largest oil companies hit headlines in the US press. On May 26, 2021, we read in *The Wall Street Journal* that *'Oil giants are dealt major defeats as climate-change pressures intensify'* and in *The New York Times* that *'Climate change activists seek seats on ExxonMobil's board'*. The reporting of this news in US media had an impact that was far from incidental. There is

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evidence that the media coverage amplified investors' perception of climate risk and led them to adopt portfolio strategies to hedge against it.

In this paper, we explore the impact of media attention to environmental issues on financial stocks. Media attention can affect investor decisions in various ways. First, greater coverage of environmental news might reflect (or lead to) a growing public awareness of environmental problems (hereafter referred to as green sentiment), especially related to climate change in the recent period. The higher the coverage, the higher may be the level of concern, and vice versa. When environmental news is covered in the economic and financial sections of newspapers, it is more likely to reflect the environmental sensitivity of investors. Since the seminal paper by Tetlock [2007], there has been a consensus on the responsiveness of investors to media coverage of economic news (see, e.g., Garcia [2013], Ke, Kelly and Xiu [2019] and Guest [2021]). Likewise, we expect an impact on environmental sentiment—an impact that could be strengthened by pro-environmental preferences on the part of asset holders or managers (see, e.g., Døskeland and Pedersen [2016], Riedl and Smeets [2017] and Hartzmark and Sussman [2019]). Second, media coverage of environmental issues might capture environmental risk (Engle, Giglio, Kelly, Lee and Stroebel [2020]), since the media pay more attention to environmental news when there is an elevated risk of, for example, ecological disasters (floods, hurricanes, wildfires, etc.) or new binding regulations to address climate change. These events covered in the media may pose physical and transitional risks to the economy and the financial system (Giglio, Kelly and Stroebel [2020]). With the reporting of such news, investors become more aware of these risks and turn away from assets (such as stocks of fossil fuel companies) with negative exposure to such hazards in favor of green assets (such as stocks in renewable energy).

Since Tetlock [2007], the measurement of economic sentiment from media sources has been widely debated, with questions surrounding which sources of information should be analyzed (e.g., newspapers versus social networks in Milas, Panagiotidis and Dergiades [2021]), whether a single or a combination of lexicons is more appropriate (e.g., Shapiro, Sudhof and Wilson [2020]), and which type of language processing should be used (dictionary-based versus machine learning algorithms with word embeddings; see, e.g., Renault [2020] and Shapiro et al. [2020]). More recently, a few papers have focused more specifically on environmental sentiment with the use of media sources. In a pioneering contribution, Engle et al. [2020] develop two climate news series through textual analysis of US sources. Their first score relies on a similarity measure between the text content of *The Wall Street Journal* and a fixed corpus of environmental texts published by various organizations. The second score is computed from the occurrence of the phrase 'climate change' in articles from various media sources with a negative tonality. Other recent contributions using text analysis include Ardia, Bluteau, Boudt and Inghelbrecht [2020], El Ouadghiri, Guesmi, Peillex and Ziegler [2021] and Bessec and Fouquau [2020]. As an alternative to textual analysis, Briere and Ramelli [2021] suggest abnormal flows into environmentally friendly ETFs as a measure of investors' taste for green assets.

In this paper, we use a dictionary-based approach to capture media coverage of environmental news and the green sensitivity of investors. For this purpose, we compile an extended lexicon on environmental issues based on various sources (thesauri on environmental issues, lexicons provided by US-based and international organizations, and glossaries provided by online encyclopedias, newspapers, research centers and universities). After stemming and lemmatization, we obtain a dictionary consisting of 745 words. This lexicon covers a larger scope than the strict issue of climate change and can be used in economic and financial contexts. With the use of this dictionary, we propose several scores measuring investors' environmental sensitivity at a weekly frequency. These scores are retrieved from four newspaper databases with different editorial lines and readerships over the last decade (the largest corpus consists of 126,944 economic and financial news articles). Our first environmental indicator measures media attention or 'buzz' as the frequency of occurrence of the environmental terms. We propose two additional sentiment indicators taking into account the tone or uncertainty of the articles, and the last score combines the three dimensions (attention, tonality and uncertainty). We also investigate the impact of the relevance and visibility of the news. Considering the different weighting schemes in the calculation of these scores and the different databases, we propose thirty different scores to disentangle the impact of attention, media tone and possible editorial bias.

These green scores should reflect environmental risk and investors' preferences for sustainable assets. To assess this hypothesis, we examine whether coverage of environmental news adversely affects the average returns and volatility of energy stocks and reinforces the taste of investors for green assets. For this purpose, we use a CAPM-GARCH model augmented with the environmental score in the mean and variance equations. To verify that both the excess returns and the conditional volatility are affected by green sentiment, we select four indices or portfolios related to the energy sector and assess how they react to changes in the scores. Symmetrically, we use four indices ranked in the green finance category. In particular, we consider two novel time series, the Paris-aligned and climate-transition indices launched by Standard and Poor's in June 2020, which have not yet been used in the literature, to the best of our knowledge. As one would expect, our results show a negative impact of media coverage on the energy indices, indicated by a reduction in the mean returns and an increase in volatility. The opposite result holds for the most climate-friendly stocks in our sample. Interestingly, energy stocks appear to be more penalized than green ones are rewarded. The impact is also stronger for the green scores taking into account the tonality of the news and those retrieved from less conservative newspapers. Overall, our findings are likely to reflect both changes in investors' expectations about firms' future cash flows and shifts in their preferences for green assets in response to greater coverage of environmental news.

This study makes several contributions to the literature. First, our study simultaneously sheds light on the impact of environmental news on stock returns and volatility. Earlier work focuses on the impact of investor sentiment on expected returns (e.g., Huynh and Xia [2020], Ardia et al. [2020] and Pástor, Stambaugh and Taylor [2021]), whereas it is mostly silent on how volatility is affected by green sentiment. In particular, Ardia et al. [2020] and Pástor et al. [2021] show a return spread between environmentally friendly and unfriendly stocks as climate concerns strengthened in media. In the general case of economic sentiment, however, Calomiris and Mamaysky [2019] suggest that when a word flow predicts positive returns, it also predicts a reduction of risk; in other words, good news increases returns and reduces risk. We obtain consistent results in the particular case of environmental news. We show that green sentiment has a negative impact on the mean returns of brown stocks and amplifies their volatility. The opposite result holds for climate-friendly stocks, in particular in the case of the two innovative green indices in our sample, the climate-transition and the Paris-aligned indices. These results confirm that investors pay increased attention to climate risk, as suggested by a recent survey among institutional investors conducted by Krueger, Sautner and Starks [2020].

Regarding the text analysis, our second contribution is to provide an extended environmental lexicon that covers several dimensions of risk in relation to investors' portfolio companies: physical, technological and regulatory risks. When relying on a dictionary-based approach, existing studies use short lists of words (El Ouadghiri et al. [2021]) and/or restrict attention to the issue of climate change (Engle et al. [2020]). Our new dictionary can be useful for future studies employing a lexical approach to retrieve green sentiment from economic and financial texts. Third, we propose new green scores that disentangle media attention to environmental news and green sentiment and that take into account the topic relevance and visibility of the information. These weekly indicators could be useful for portfolio and risk management, as they provide a relevant metric of climate risk exposure. Sustainable investors could employ them to screen financial assets and divest themselves from (or underweight) assets that are more sensitive to this measure of risk. A final contribution is to investigate the impact of the editorial line on green sentiment by considering several datasets of newspapers with different political slants and readerships. Interestingly, restricting the corpus of texts to conservative newspapers mitigates the impact of the coverage of environmental news on financial markets. This complements the literature on media representation of climate change (Chinn, Hart and Soroka [2020]). However, considering too many newspapers is a source of noise.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the financial and text data. Section 4 provides the estimation results and some robustness tests. The last section concludes.

2 Review of the literature

There is a burgeoning literature on textual measures of green sentiment based on media sources. Engle et al. [2020] develop two climate news series through textual analysis of newspapers. Their first score is based on a measure of similarity between the text content of *The Wall Street Journal* 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 that contain the phrase 'climate change' and that have been assigned to a negative sentiment category by a data analytics vendor. El Ouadghiri et al. [2021] propose measuring media attention by computing the number of articles in four major US newspapers featuring the terms 'climate change' or 'pollution'. Bessec and Fouquau [2020] capture the environmental sensitivity of US investors by computing the occurrence of environmental words in the economic and financial sections of *The Wall Street Journal*. They use an extended lexicon covering environmental issues compiled with a recursive algorithm to search for synonyms and antonyms. They also distinguish the impacts of local and worldwide news. Ardia et al. [2020] propose a measure of climate change sentiment retrieved from eight US newspapers. They count the occurrence of negative and risk terms in a selection of articles classified in the climate change category by the data providers to capture the level of negativity as well as the degree of uncertainty and risk in the coverage of climate change. They combine these two dimensions into a unique score and then aggregate this score at daily frequency for each newspaper and across newspapers. Except for this last paper, the literature does not make a clear distinction between media attention and media concern about climate change. We address this gap by separately measuring attention and the negativity and uncertainty of environmental news coverage. We also propose an aggregate measure. Overall, we compare thirty different measures of media attention and media sentiment in a common framework. We also complement this literature by investigating a possible impact of the editorial line of the media sources.

Regarding media representation of climate change, a large body of literature has explored partisan differences among newspapers in regard to their coverage of climate change. In the particular case of the United States, Feldman, Hart and Milosevic [2017] compare climate change reporting in *The New York Times*, *USA Today*, *The Washington Post* and *The Wall Street Journal*. They point out systematic differences. *The Wall Street Journal* is the least likely to discuss the impact and threat posed by climate change and the most likely to highlight the low efficacy and negative economic impact of regulations addressing climate change. Hart and Feldman [2014] report similar results on television broadcasts by CNN and MSNBC versus Fox news. Chinn et al. [2020] examine the climate change news coverage of 11 national and regional US newspapers over more than thirty years. Using dictionary and unsupervised machine-learning content-analytic methods, they point to increasing politicization (evidenced by an increase in mentions of political actors instead of scientists in the news coverage) and polarization in newspaper coverage of climate change (see also Bolsen and Shapiro [2018] on this last point). Bohr [2020] conducts a large-scale analysis of the partisan division in the environmental coverage of 52 US newspapers and shows some partisan differences in coverage of some topics (e.g., conservative outlets pay more attention to the 'climategate' scandal, while liberal outlets pay more attention to the Arctic region and energy infrastructures). In line with these works, we might expect some variation in the impact of environmental coverage on the green sensitivity of investors depending on the media sources.

Other related studies document that green stocks outperform stocks of carbon-intensive firms when climate concerns increase and that media can contribute to this increase. Pástor, Stambaugh and Taylor [2020] provide a theoretical model predicting that green assets have lower *expected* returns than brown assets while they can have higher *realized* returns in periods of unexpected increases in demand for green products (or a decrease in brown assets). This shift in demand may be due to increased concerns about climate issues. Pástor et al. [2021] provide empirical support for this model. After constructing a theoretically motivated green factor from US stock data, they show that green stock outperformance disappears when a text-based measure of media concern about climate change is controlled for. Unexpected shifts in environmental regulation can act as another source of environmental shocks (Hsu, Li and Tsou [2020]). In this vein, Choi, Gao and Jiang [2020] find evidence that investors pay more attention to climate change when the local temperature is abnormally high and that stocks of carbon-intensive firms underperform those of firms with low carbon emissions in abnormally warm weather. They argue that this underperformance could be amplified by greater media coverage of climate change during these abnormal episodes. Hong, Li and Xu [2019] show that stock prices of food companies (food processing, beverage and agricultural companies) respond to trends in droughts across the world. They construct a measure of countries' vulnerability to drought as a result of climate change and show that food stocks have lower excess returns in the most vulnerable countries.

The extant literature on green sentiment (or media attention to environmental news) focuses on first-moment contemporaneous correlations between returns and sentiment (Huynh and Xia [2020], Ardia et al. [2020] and Pástor et al. [2021]) and neglects the correlation with higher moments such as volatility. In contrast, many researchers have explored how general economic sentiment assessed through news, social media, search volume or financial key indicators affects stock market volatility (e.g., Antweiler and Frank [2004], Behrendt and Schmidt [2018], Calomiris and Mamaysky [2019]) and helps predict it (e.g., Song, Ji, Du and Geng [2019], Ye, Hu, He, Ouyang and Wen [2020] and Xiao and Wang [2021] in the specific case of oil prices). In the context of shares of renewable-energy companies, Reboredo and Ugolini [2018] find that Twitter sentiment divergence has notable effects on price volatility and trading volumes. In this strand of the literature investigating the impact of general economic sentiment on financial markets, numerous studies document that negative (positive) sentiment increases (reduces) stock volatility (Lee, Jiang and Indro [2002], Kumari and Mahakud [2015], Johnman, Vanstone and Gepp [2018] and Calomiris and Mamaysky [2019]). On this basis, we expect a positive effect of environmental concerns on the volatility of brown stocks and a reduction in green assets.

3 Financial and text data

3.1 Green/brown financial indices

We assess the impact of environmental news on eight stock indices: four green indices that cover firms with good environmental performance and four brown indices related to the energy sector. Seven of these indices are subindices of the S&P500, in line with the paper's US focus, whereas the last index has a larger geographical coverage. The main characteristics of the variables and the parent indices are reported in Table 1.[1]

The group of green indices includes the *S&P500 climate-transition index* and the *S&P500 Paris-aligned climate index* (hereafter referred to as *climate-transition* and *Paris-aligned*), which are the most likely to react to environmental news. These two indices were launched in June 2020 and were retropolated until 2017. They incorporate the S&P500 constituents that are compatible with the 1.5°C global warning climate scenario of the Paris Agreement at the index level. The constituents are also selected and weighted according to their exposure to the transition and physical risks without omission of the possibility of greenwashing. The eligibility criteria are stricter for the stocks in the Paris-aligned index. It includes 349 components, in comparison to the 387 of the climate-transition index. As shown in Table 1, the firms within these indices do not release any fossil fuel reserve emissions[2] and have a low weighted average carbon intensity.[3] The third green index, the *S&P500 fossil fuel free index* (*fossil fuel free* hereafter), is available over a longer period (from January 2012). This index includes 490 constituents of the S&P500 that do not own fossil fuel reserves. Note, however, that their weighted average carbon intensity is quite similar to that of the whole S&P500. The last indicator in the green category is the *S&P500 ESG exclusions II index* (*ESG* hereafter). This index is not restricted to satisfying environmental criteria only. It includes 485 S&P500 firms that are not involved in the controversial weapons, small arms, tobacco products or thermal coal industries. This can explain why the weighted average carbon intensity of this index is similar to that of the S&P 500 overall and why these firms' fossil fuel reserve emissions are slightly higher. We therefore expect a lower impact of environmental news on this measure in our empirical analysis.

The brown group includes four stock indices related to the energy sector. First, we consider the *S&P500 energy index*, which incorporates 24 of the S&P500 constituents in the energy sector according to the GICS classification. This index has a lower total market capitalization than those of the other indices (see Table 1). For the environmental characteristics, the weighted average carbon intensity is 3.5 times that of the S&P500 index and 9.5 times that of the Paris-aligned index. The fossil fuel reserve emissions are

[1] Additional details can be found on the S&P website `https://www.spglobal.com/spdji/en/`.

[2] This carbon exposure metric is provided by S&P Global. The indicator represents the carbon footprint that could result from the burning of the fossil fuel reserves owned by the index constituents. It is calculated by dividing the aggregated emissions by the total value invested in the index in millions of US dollars. See `https://www.spglobal.com/spdji/en/documents/additional-material/spdji-esg-carbon-metrics.pdf`.

[3] This metric captures the carbon intensity of the index. It is calculated as the sum of the carbon intensity of each component (emissions per USD 1 million of revenue generated) weighted by the size of the component in the index.

also much higher. The second index is the *S&P commodity producer oil and gas exploration and production index* (*SP global oil & gas* hereafter). It includes 45 firms located in nine countries for a total market cap of close to USD 422 billion. Not surprisingly, the ESG carbon indicators deteriorated even more in this group. A major drawback of this index for our analysis is that it does not exclusively focus on the US market, even though US firms account for 56% of the total market cap. To circumvent this issue, we construct two additional portfolios. The first one (denoted as *SP500 oil & gas*) includes the twelve US companies in the S&P500 that are classified in the 'commodity producer oil and gas exploration and production' subcategory.[4] The individual components are weighted according to their relative market capitalization as done in the S&P500. The second portfolio (*brown energy*) incorporates highly polluting US companies in the energy and utility sectors according to the Newsweek green ranking. We select the ten lowest-ranked companies on the environmental component of the Newsweek score in the energy and utility category.[5] Again, the ten firms are aggregated with respect to their market capitalization.

We download the stock data from Bloomberg. The returns are taken at weekly frequency: we collect the prices on Friday (or other end-of-week), and we compute the returns as the log difference. We then take returns in excess of the one-month Treasury bill rate available from Kenneth French's website. The sample starts in January 2010, when the stock prices became available, and ends in January 2020 to avoid the exceptional effect of the COVID-19 pandemic. Our exclusive focus on the most recent decade reflects investors' recent awareness of environmental issues, particularly global warming (as shown, for instance, by Bolton and Kacperczyk [2021]), as well as data availability constraints.

3.2 Environmental scores

3.2.1 Text source

To measure coverage of environmental issues in the US press, we collect articles published in four leading newspapers and archived in the *Factiva* database.

We use a selection of articles published in *The New York Times*, *USA Today*, *The*

[4]The 13th company in this subcategory, *Diamondback Energy*, is excluded since its data are not available for the whole period and its capitalization is low.

[5]The ranking is available at `https://www.newsweek.com/americas-most-responsible-companies-2021/energy-utilities`. The ten companies include five oil and gas companies (Apache, Chevron, Devon Energy, EOG Resources and Marathon Oil) and five electric and natural gas utilities (Dominion Energy, AES, CMS Energy, CenterPoint Energy and American Electric Power Company). We exclude Xcel Energy, as its data are available from January 2018 only.

Washington Post and *The Wall Street Journal* (NYT, USA, WP and WSJ hereafter). These four national newspapers are distributed on a daily basis on weekdays, and some of them come out on weekends as well (WSJ on Saturday, NYT and WP additionally on Sunday). In addition to being among the most read newspapers in the United States (based on their average weekday print circulations at the beginning of 2020), they cover a large spectrum of ideological slants and readerships (with NYT being the most liberal and WSJ the most conservative).[6] This diversity might help avoid a possible bias in our analysis arising from liberal newspapers being more concerned about climate change and more supportive of actions taken to address it than conservative ones (Feldman et al. [2017]).

To assess the impact of media coverage on financial markets, we focus on a selection of articles ranked in two subject categories by *Factiva*: *commodity/financial market news* and *economic news*. Their content is more likely to affect the environmental sensitivity of investors and influence their decisions. We collected articles from January 2010 to January 2020. The selection contains 126,944 articles after we remove 869 identical replicates. As shown in Figure 1, 60% of the papers in our corpus are published in WSJ and approximately 20% in NYT. In the following, we consider three alternative sets of newspapers to identify a possible effect of the slant of their editorial boards and readerships: only WSJ, with its relatively conservative content; WSJ augmented with NYT, to have a more balanced editorial view; and the whole set of newspapers (NYT, USA, WP and WSJ).

3.2.2 Environmental dictionary

To measure media attention to environmental issues, we use a dictionary-based approach: we count the occurrence of terms related to environmental topics in our selection of articles. For this purpose, we need a dictionary of environmental terms.

To obtain an exhaustive list of terms, we use a large number of sources. We consider lexicons provided by various organizations; thesauri on environmental issues such as the General Multilingual Environmental Thesaurus, developed for the European Environment Agency; glossaries provided by online encyclopedias; lexicons provided by newspapers; and glossaries provided by research centers and universities. The full list is provided in Appendix 1. When we merge these lexicons, we obtain a list of 3257 terms (2940 terms after duplicates are removed).

To capture all possible inflections of the terms in the text, we reduce each term in the

[6]See, for instance, the slant index of US daily newspapers in Gentzkow and Shapiro [2010].

initial list to its root when possible (e.g., pollut- for pollution, polluting, polluter, and pollutant). This stemmization procedure leads to the removal of several terms containing the same root. Moreover, we also discard words that can be used in other contexts in economic and financial texts (e.g., certification, emission), or we consider some bigrams to avoid misleading uses (e.g., green funds and green energy instead of simply green as used, for example, in many other contexts such as greenback, green light, and green card). Finally, we add the names of the main environmental organizations and their acronyms. The final list consists of 745 terms and is reported in Appendix 2.

3.2.3 Environmental scores

To capture media coverage of environmental issues, we derive several measures with our lexicon. The first score measures media attention to environmental news, and two others reflect the tonality and uncertainty of this coverage. The final score aggregates these components.

The first measure of environmental media coverage (*buzz*) quantifies the attention dedicated to environmental issues in the newspapers regardless of the tone. It is calculated as the frequency of environmental words per article published during a week t:

$$buzz_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \omega_i NE_{i,t} \tag{1}$$

where N_t is the number of articles published during week t, $NE_{i,t}$ is the number of environmental words in article i published during week t and ω_i is the weight for article i. A higher value of this score reflects a higher flow of environmental words in the print media and subsequently greater attention devoted to environmental topics.

We assign three possible weights ω_i to each article. In addition to the *uniform* scheme giving an equal weight $\omega_i^{(1)} = 1$ to each article i, we consider two additional weights:

$$\omega_i^{(2)} = \log\left(N_k/FP_k\right) \quad \text{if article } i \text{ is published on the front page, 1 otherwise}$$
$$\omega_i^{(3)} = \log\left(N_k/TLP_k\right) \quad \text{if article } i \text{ starts with environmental word(s), 1 otherwise}$$

where FP_k is the number of articles published on the front page of newspaper k, TLP_k the number of articles in newspaper k whose title or leading paragraph contains an environmental word and N_k the total number of articles for newspaper k. In the second case (*visible* weight), a higher weight is assigned to an article released on the front page of the newspaper. Such articles are more visible and hence probably more influential.[7] In the last case (*relevant* weight), a higher weight is given to an article if the title or the leading paragraph (as defined by Factiva) contains an environmental word. Such articles are more likely to deal with environmental issues and therefore to affect the environmental sensitivity of investors.

The buzz score is a simple measure of the attention dedicated to environmental issues in the newspaper. Since it quantifies the flows of environmental words in articles, it might aggregate positive and negative environmental news or news leading to higher or lower environmental risks. This could mitigate the impact of environmental news. To address this possible concern, we develop two alternative scores. We still use Equation (1) but in a more restricted set of articles. The first variant (*tonality*) is computed based on articles with a negative tonality, and the second variant (*uncertainty*) is computed based on articles in which the coverage of environmental news is characterized by uncertainty. We expect that a pessimistic or an ambiguous tone leads to a higher perception of climate risk and thereby results in higher market volatility.

To identify articles with a negative or an uncertain tonality, we use the lexicons compiled by Loughran and McDonald [2011] (LM hereafter). Their lexicons are shown to be better suited to parsing financial texts than other lexicons developed in more general contexts. LM provide lists of negative (2355), positive (354) and uncertain (297) terms for financial applications.[8] The negative list includes terms such as *adverse*, *bad*, *damage*, and *warning*, while the positive list incorporates terms such as *advance*, *best*, *progress* and success. Examples of uncertain terms are *approximate*, *could*, *doubt*, and *probable*, which are typically used in imprecise formulations or when the consequences are not well established. In our analysis, an article is classified as negative when the number of negative words in the text exceeds the number of positive words, and it is classified as uncertain when we find at least one uncertain word in the article. We exclude the other articles. By doing so, we cover environmental news associated with an increased environmental risk. In the robustness section, we consider an alternative way to capture uncertainty in the coverage with weights proportional to the number of uncertain words in the text.

Finally, we propose a score that summarizes the three dimensions (attention, tonality and uncertainty). More precisely, we conduct a principal component analysis (PCA) of

[7]We follow Fedyk [2018], who shows that a higher positioning of economic news on the Bloomberg terminal leads to higher trading volumes and larger price changes in financial markets.

[8]The lexicons are available at `https://sraf.nd.edu/textual-analysis/resources/`. We use the updated version from March 2019.

the nine scores. This procedure allows us to check whether financial markets react more to a common trend capturing the three dimensions or, as we would expect, if they are more responsive to negative and relevant news.

Overall, we obtain ten scores and compute them on three possible sets of newspapers. These thirty scores are computed at weekly frequency. All text analyses were run with Python with the *Natural Language Tool Kit* (NLTK) package. In our computation, a week t includes the five weekdays and the previous weekend (for the three newspapers released on weekends). Since financial markets are closed on weekends, the articles published on the weekend affect the stock prices on the next Monday and therefore should be associated with the weekdays of the week after (as seen previously, the financial returns are computed from the log-difference of prices on two consecutive Fridays).

4 Media coverage of environmental news and market reaction

4.1 Media attention and green sentiment

To obtain measures of media attention to environmental issues, we use our lexicon, and we count the occurrence of environmental terms in the four newspapers.

We start with some descriptive statistics. Figure 2 depicts the proportion of articles in each source with at least one environmental word. Over the whole period, more than one-fifth of the articles published in the economic and financial sections of WSJ and WP contained an environmental word, against 15% in USA and WSJ. Figure 3 depicts the most frequently appearing words from the environmental lexicon in the corpus. The top five consist of environmental, carbon, climate change, pollut- and hurricane. The terms in the word cloud reflect the two dimensions of climate risk to investors' portfolios as discussed by Giglio et al. [2020]: physical risk (damages caused by extreme climate phenomena and physical changes of the planet induced by global warming) and transition risk (cost of adjustment to a low-carbon economy). The most highlighted risk in our selection is the physical component with the terms climate change, hurricane, global warming, wildfire, natural disaster; the second dimension is also present with terms related to technological innovations (e.g., electric vehicle, solar power, wind power, clean energy) or regulatory changes (e.g., Environmental Protection Agency or EPA, cap and trade, recycle).

As explained above, we measure three dimensions in the media coverage of environmental issues: attention, tonality and uncertainty. The last score aggregates the three components. Figure 4 depicts the four scores. For parsimony, we plot only the scores retrieved from the whole set of newspapers and the first three scores with uniform weights.[9] The peaks in the graphs coincide with serious environmental disasters (e.g., Fukushima in March 2011, hurricanes Harvey and Irma in September 2017 and, more recently, wildfires in California and Australia).[10] The scores also show peaks during environmental summits (for example, COP 21 in Paris in late 2015) or when the EPA announces new environmental regulations to reduce carbon emissions (for instance, the Clean Power Plan, first proposed in June 2014 and designed to reduce pollution from existing power plants). Coverage of these events may spread over several weeks, as in, for example, the cases of COP 21 and hurricanes Harvey and Irma. Overall, the scores peak when the environmental risk (physical/transition) is high. This trend can explain why scores taking into account media tone are close to the buzz score.

To elaborate further on the proximity of the three components, we perform a correlation analysis. The buzz, tonality and uncertainty scores are computed on three sets of newspapers, with articles weighted either uniformly or according to their relevance and visibility. As expected, the correlation measured with a Pearson coefficient is positive and significant. The average correlation of the 27 indicators is 0.80. The minimum correlation (0.52) is obtained for two indicators that differ by construction: the tonality indicator on WSJ with relevant weights and the buzz indicator on the whole corpus of newspapers with uniform weights. Another illustration of the strong correlation of the scores is the large fraction of variance in each newspaper dataset captured on average by the first principal component (90%). We investigate in the following whether it remains necessary to disentangle media coverage and media sentiment in the particular case of environmental news.

4.2 Stock reaction to media coverage of environmental issues

We assess the impact of media attention to environmental news on the excess returns and risk of the brown and green indices.

We estimate a CAPM-GARCH model augmented with the environmental score for

[9]The other graphs are available upon request.

[10]There are several case studies establishing a drop in the valuations of specific firms known to be responsible for pollution at the time of disclosures of offenses (e.g., Hamilton [1995] and Capelle-Blancard and Laguna [2010]).

each of the eight indices/portfolios:

$$\begin{cases} R_{it} - R_{ft} = \alpha_i + \beta_i \left(R_{mt} - R_{ft}\right) + \delta_{1i} MEDIA_t + \sigma_{it}\varepsilon_{it} \\ \sigma_{it}^2 = b_0 + b_{1i}\varepsilon_{i,t-1}^2 + b_{2i}\sigma_{i,t-1}^2 + \delta_{2i} MEDIA_t \end{cases}$$

In the first equation above, R_{it} is the weekly return of stock index i in week t, R_{ft} the risk-free rate, R_{mt} the stock market return and $MEDIA_t$ one of the previously discussed media scores. As a stock market index, we use the S&P global for the S&P global oil and gas index and the S&P500 for the seven other indices. This first equation is the baseline CAPM model augmented with the media score. In the second equation, we use a GARCH specification (Engle [1982] and Bollerslev [1986]) augmented with the environmental score to model the conditional volatility σ_{it}^2 of the residuals ε_{it}. The coefficients of interest are δ_{1i} and δ_{2i} in the first and second equations. We expect that a rise in attention to environmental news reduces the excess returns of polluting stocks and leads to an upward revision of their volatility, that is, $\delta_{1i} < 0$ and $\delta_{2i} > 0$, and the opposite for green indices.

We use the method of maximum likelihood to estimate the model on the eight indices/portfolios. Adding an exogenous term in the variance equation complicates convergence of the algorithm. To avoid nonconvergence issues, we implement the Gauss-Newton algorithm with Marquardt steps as an optimization method.[11] This exercise is replicated for the aggregate score and the three components (buzz, tonality and uncertainty) calculated with the three possible weights (uniform, visible and relevant) on the three sets of newspapers. To obtain an overall picture of the impact of media coverage of environmental news on the stock indices, Table 2 provides the z-statistics of the environmental coefficients (δ_1 and δ_2) in the mean and variance equations. The cells are highlighted red when greater coverage has a negative impact on the index (i.e., a significant and negative impact on the returns or a significant increase in volatility). Conversely, we use green cells for significant excess returns or a significant decrease in volatility in response to more coverage. We use a 10% significance level in the tests.

Overall, there is a strong effect of the environmental scores on the brown stocks and to a lesser extent on the green indices (60% of the significant coefficients with the expected signs correspond to brown stocks versus 40% to green ones). The impact on volatility is clearer, while the returns are less sensitive to greater coverage of environmental news (with 60% of the significant coefficients with the expected sign corresponding to the former versus 41% to the latter). When significant, the effect on the returns has the

[11]The GARCH model is estimated with the software *Eviews* with the option *Eviews Legacy* in the estimation options.

expected sign in most cases: there is an increase (decrease) in green (brown) returns in response to greater media coverage/concern. This finding is consistent with two recent theoretical contributions, Hsu et al. [2020] and Pástor et al. [2020], showing that 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 (Pástor et al. [2020]). As expected, a positive shift in green sentiment is also associated with a significant increase in the volatility of brown indices, while the fluctuations in green indices decrease. One notable exception in the green selection is the ESG index, which is rarely affected. This finding may be related to the construction of the index described previously (the ESG index consists of a selection of stocks based on a larger set of criteria than only environmental ones, as shown by the lower environmental performance of this index in Table 1). These first conclusions are relatively robust across the various exercises in Table 2, even though some interesting findings emerge from the comparison of the alternative corpus, scores and weights.

We consider three alternative sets of newspapers to compute the environmental scores. If we sort them according to the number of significant coefficients with the expected signs, we obtain the following ranking: first WSJ and NYT (89 expected coefficients out of 160), followed by WSJ (83 expected coefficients) and the whole corpus (69). Interestingly, considering only WSJ deteriorates the results in comparison to those for WSJ and NYT. This underperformance might be related to the more climate-skeptical editorial line of WSJ (Feldman et al. [2017]). WSJ has been shown to be less likely to discuss the impact and threat posed by climate change than the three other newspapers, and this should attenuate the impact of the environmental scores retrieved from this newspaper. However, there is still a significant impact for WSJ alone given the leading role of the newspaper in the US economic press and its influence on financial markets (see, among others, Tetlock [2007], Manela and Moreira [2017] and Madsen and Niessner [2019]). To assess this conjecture, we also estimate the models without WSJ in our dataset, and the results strongly deteriorate.[12] Symmetrically, considering more generalist outlets, such as USA and WP, might introduce some noise in the measure of media coverage. This could explain why the environmental factor is less influential when it is retrieved from the whole set of newspapers.

The common trend of the three scores (buzz, tonality and uncertainty) captured by PCA is influential, especially on the brown stocks (71% of the significant coefficients in the last column of Table 2). To go further, we compare the results for the three components

[12]These results are available upon request.

to investigate whether the tonality or uncertainty of the news coverage amplifies the reaction of the market over a simple measure of attention. As discussed previously, our conclusions are based on the number of significant coefficients with the expected signs net of number of those with the wrong ones. On this basis, the tonality score ranks first (67 correct coefficients), followed by the uncertainty score (59) and finally the buzz score (58). Hence, taking into account the tonality and to a lesser extent the uncertainty of the information improves the results with respect to simple measures of attention. This is especially relevant for the variance equation. However, the buzz score is influential in a number of cases, which shows that environmental news is frequently reported in negative or uncertain contexts: news related to climate change, environmental disasters, discussion of new environmental regulations, etc. Engle et al. [2020] also mention this point when they construct climate change indicators to hedge financial portfolios.

In addition to the uniform system, we use several weighting schemes for the articles based on their visibility or the relevance of the news. The difference is not straightforward. The visibility- and relevance-focused systems show a slightly superior performance (64 correct signs net of the wrong ones for the visibility scheme and 63 for the relevance one against 57 with uniform weights). In particular, the relevance weights lead to a higher change in volatility (45 for the relevance system versus 31 for the visibility system and 25 with uniform weights). In summary, the scores are more influential when they are retrieved from WSJ and NYT, the tonality score performs better overall, and the two weighting schemes—with visibility and relevance weights—are close competitors in terms of performance. Our last comparison is between the aggregate score given by the PCA and our best component (tonality with relevance weights). This aggregate score, which requires a prior estimation of the nine components, does not improve the net number of significant coefficients. Accordingly, we conclude that a unique component is able to capture the reaction of the market, and in particular, tonality is highly influential for stock volatility. However, in all settings, we obtain similar results, which proves their robustness.

To pursue our analysis, we go over the results index by index. We have pointed out previously that media coverage of environmental news has an adverse effect on energy indices/portfolios. This conclusion is valid for the four brown series with a significant impact on volatility and/or the return. The effect is particularly strong on S&P500 oil and gas and S&P500 energy. The less affected portfolio is the brown portfolio, which mixes energy and utilities, where there has been a general switch from coal to less polluting sources of energy over the past decade in the United States. For the green indices, the impact of media coverage can be related to these firms' environmental performance. In regard to the two indices grouping the lowest carbon emitters in our selection, media coverage reduces volatility in all cases for the climate-transition index and in 26 cases out of 30 for the Paris-aligned index. The returns for this last index also increase significantly in some cases for the dataset with the best performing newspapers (WSJ and NYT). The results for the fossil fuel free index are more modest. Returns always react positively to environmental news, but volatility is also amplified. As mentioned before, this index has mixed environmental characteristics, with no fossil fuel reserve emissions but at the same time a high carbon intensity (quite similar to that of the entire S&P500 index). Likewise, media coverage has a low effect on the ESG index, with its mixed environmental performance as explained above.

Table 3a-b gives the estimated coefficients, their p-values and the R-squared of the models. We provide the results based on two settings as discussed above: the tonality score calculated on WSJ and NYT with two possible weights, the visibility and relevance weights. We also test the specification of the mean and variance equations. The null hypothesis of no remaining serial correlation in the standardized residuals or standardized squared residuals is generally not rejected.[13] Therefore, there is no remaining correlation in the mean equation and no remaining ARCH in the variance equation. Using the visibility or relevance weights does not modify the value of the estimated parameters. The beta coefficients are clearly above one for the first three brown series. This result is not surprising given the large individual betas in the energy sector.[14] The lowest beta for the brown portfolio based on the Newsweek ranking is due to the lowest individual coefficients of the included utilities. In contrast, the estimated betas of the green indices are closer to one, which can be explained by the higher number of constituents (see Table 1). Finally, the coefficients of the environmental score δ_1 and δ_2 are more often significant for the brown indices than for the green indices, as discussed above. It is also interesting to note that the magnitude of the coefficients is generally much larger for the former than for the latter. This result is consistent with Ardia et al. [2020] and suggests that investors tend to divest from firms with high emissions (Bolton and Kacperczyk [2021]) to reinvest in the rest of the market, not only in green stocks. It also suggests that the construction of green indices relies more on an exclusionary screening of brown stocks

[13]The inclusion of an autoregressive term in the mean equation for the Paris-aligned index and an increase in the order of the GARCH specification for the SP500 oil and gas do not modify the significance of the score.

[14]For example, the weekly betas relative to the S&P500 from 2010 to 2020 are 1.05 for Chevron Corp, 1.11 for ConocoPhillips, 1.22 for EOG Resources, 1.33 for Schlumberger N.V., 1.37 for Marathon Petroleum Corp, and 1.60 for Hess Corp (source: Bloomberg).

than on a selection of the most virtuous ones.

Finally, we check the robustness of our results with the last three exercises: we consider the first axis of a PCA as a summary of all scores and on all corpora, a dataset excluding the articles published on weekends and an alternative measure of uncertainty. For comparison with Table 2, we report the z-statistics of the environmental coefficients in Table 4. When we consider the first axis of a PCA as a summary of the 27 possible scores, we obtain the same picture of a negative impact on the brown indices and a positive effect on the green indices. With respect to the best benchmark (tonality score with relevance weights on the NYT and WSJ dataset), we lose one significant coefficient. Second, we exclude the news published during weekends. This exercise is useful for assessing whether the reading of newspapers during the weekend has a different influence on the markets. The comparison of the two sets of results, with or without weekends, does not show a noticeable weekend effect for environmental news, even though removing the articles published on weekends slightly improves the results. This omission may lead to more homogeneous data (news published during weekends might be different or differently presented, and WSJ is not published on Sundays). Last, we use an alternative measure of uncertainty. In addition to excluding articles without uncertain words, we assign a weight proportional to the number of uncertain words in the text for the remaining articles. Again, the pattern is quite similar, with a slightly higher number of significant coefficients.

5 Conclusion

In this paper, we assess the sensitivity of financial markets to media coverage of environmental news. Using a dictionary-based approach with a new environmental lexicon, we develop several measures of such media coverage and measures of its tonality and uncertainty.

A clear result emerges for all indicators: greater coverage of environmental news has a strong adverse impact on the returns and volatility of brown indices, whereas the most virtuous green indices are positively affected. We establish that these results are particularly strong for specific environmental indicators. We first show that the impact of the green score is dependent on the considered newspapers. Restricting the dataset to *The Wall Street Journal* diminishes the impact. However, extending the database to the entire corpus adds noise. Second, we show that media sentiment and, more precisely, media tone capture market volatility more accurately than does a basic measure of media coverage. Finally, the visibility and relevance of newspaper articles affect the market reaction.

From a managerial perspective, the green indicators developed in this paper could be a useful metric of asset exposure to climate risk. As a direct extension of this project, we aim to predict the volatility of the market with the help of these indicators, in the spirit of recent studies performing this exercise with measures of economic sentiment.

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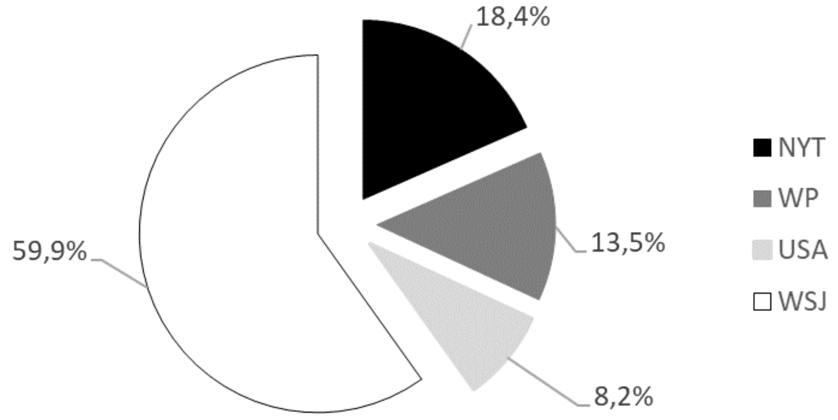
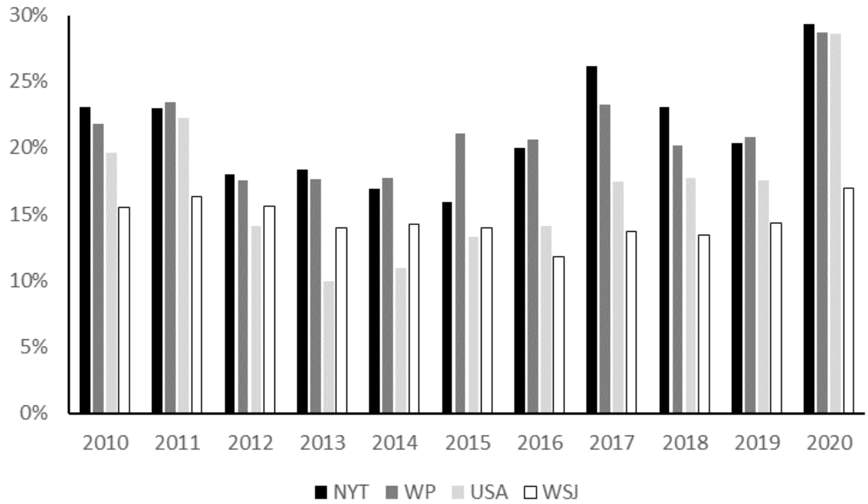
Figure 1: Composition of the corpus



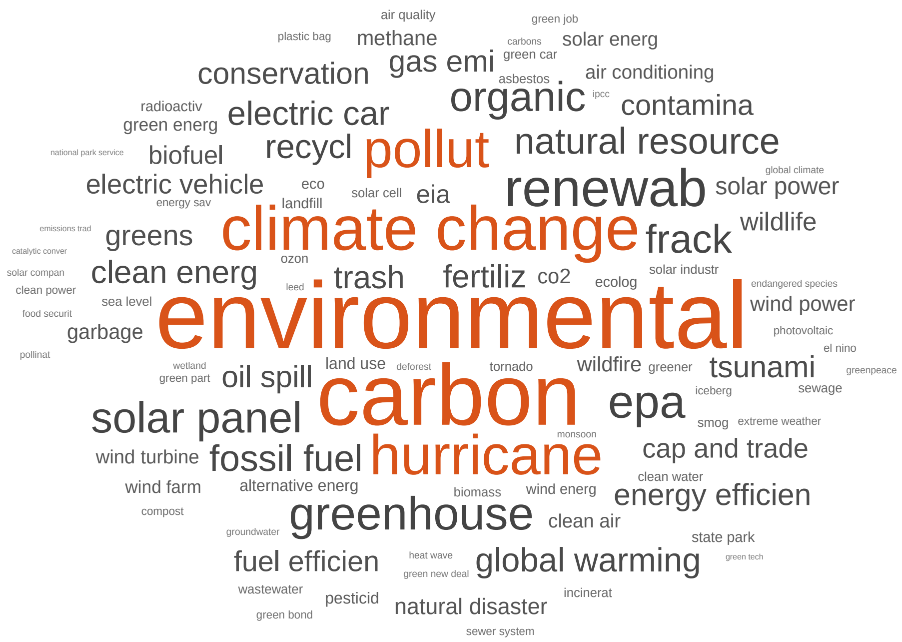
Note: This figure depicts the proportion of articles in the dataset published in the four newspapers.

Figure 2: Proportion of articles including at least one environmental word



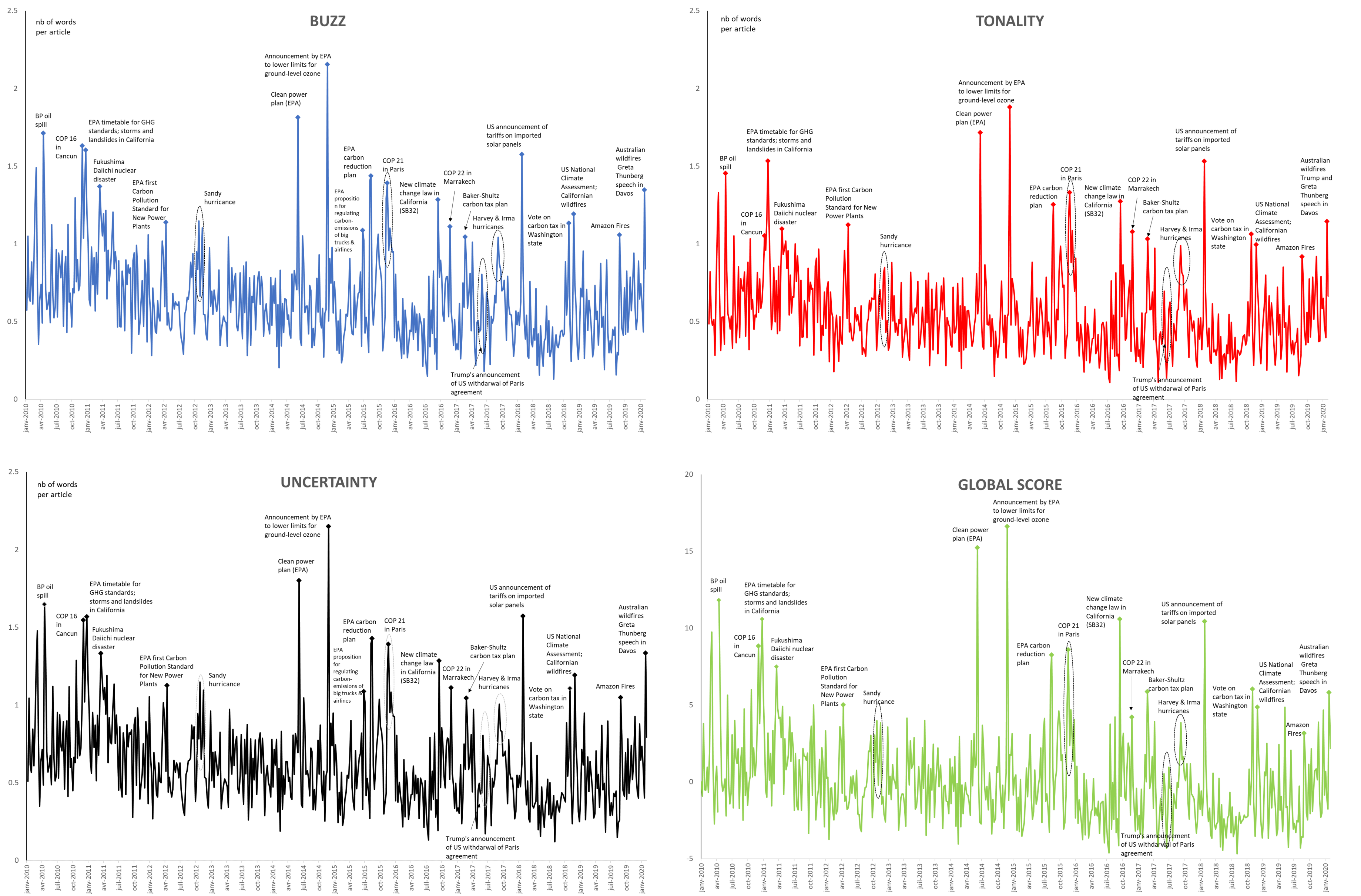
Note: This figure depicts the proportion of articles in our corpus that include at least one word in our environmental dictionary. For 2020, the frequencies are calculated based on articles released in January only.

Figure 3: Most frequent words in the corpus



Note: This figure depicts the most frequently appearing words from the environmental dictionary in our sample of articles (published in the four newspapers).

Figure 4: Weekly environmental scores (2010-2020)



Note: This figure plots the buzz, tonality, uncertainty and aggregate scores derived from the whole corpus. The first 3 scores are computed with uniform weights.

Table 1: Stock indices

	Bloomberg Code	Area	♯ of constituents	Total Market Cap	Weighed average carbon intensity[1]	Fossil fuel reserve emissions[2]	First value
Climate-transition	SP50CTUP	US	387	27 033 005	105.36	0	2016.12
Paris-aligned	SP50PAUP	US	349	26 276 855	67.14	0	2016.12
Fossil fuel free	SP5F3UP	US	490	31 721 136	180.46	0	2011.12
ESG	SPXCX2UP	US	485	31 501 714	190.25	512.55	2009.06
SP500 energy	SPN	US	24	767 532	651.81	20 123.82	1989.09
SP global oil & gas	SPCPOG	Global[3]	45	421 892	760.91	57 755.64	2005.12
SP500 oil & gas	N/A	US	12	N/A	N/A	N/A	2010.01
Brown energy	N/A	US	10	N/A	N/A	N/A	2010.01
S&P 500	SPX	US	505	37 267 249	184.55	459.02	1928.01
S&P global	SBBMGLU	Global[4]	12 636	104 494 666	225.5	1 851.19	1992.12

Notes: (1) in metric tons of CO_2e by \$1M of revenues, (2) in metric tons of CO_2e by \$1M invested, (3) 9 developed countries (US, Canada, Australia, Russia, China, Japan, Sweden, Norway, UK), (4) 50 developed and developing countries.

Table 2: Impact of the green scores on the stock indices

			Buzz			Tonality			Uncertainty			PCA
			uniform	visible	relevant	uniform	visible	relevant	uniform	visible	relevant	
ALL	SP500 energy	return	-1.87	-1.83	-1.17	-2.07	-2.03	-1.31	-1.84	-1.80	-1.15	-1.82
		variance	1.14	1.25	1.68	1.55	1.62	2.63	1.26	1.35	1.84	1.56
	SP global oil & gas	return	-1.97	-1.91	-1.41	-2.12	-2.06	-1.33	-1.93	-1.87	-1.32	-1.92
		variance	1.71	1.85	3.39	1.90	2.08	4.20	1.84	1.97	3.66	2.42
	SP500 oil & gas	return	0.72	0.69	0.60	0.59	0.79	0.38	1.23	0.95	0.63	-0.01
		variance	3.29	2.05	278.40	9.04	63.58	3.11	0.71	22.09	4.68	2.91
	Brown energy	return	-1.56	-1.50	-1.34	-1.12	-1.15	-0.68	-1.55	-1.48	-1.35	-0.29
		variance	0.75	0.85	1.40	1.00	1.08	1.82	0.81	0.91	1.51	3.18
WSJ	SP500 energy	return	-3.33	-3.31	-2.39	-3.56	-3.51	-2.49	-3.22	-3.20	-2.33	-3.25
		variance	1.48	1.77	2.37	1.87	2.26	2.77	1.63	1.91	2.51	2.10
	SP global oil & gas	return	-1.51	-2.00	-0.62	-1.66	-2.87	0.16	-0.70	-1.19	0.18	-1.93
		variance	112.39	5.16	6.74	5.59	7.64	93.57	248.31	113.82	7.12	7.72
	SP500 oil & gas	return	-0.37	0.44	-0.86	0.72	-1.97	-0.22	0.65	0.05	-0.06	-1.10
		variance	6.25	5.73	-0.51	2.74	2.92	1.82	2.80	2.22	4.73	2.34
	Brown energy	return	-4.05	-3.93	-2.59	-3.43	-3.33	-2.17	-4.10	-3.95	-2.62	-3.59
		variance	0.69	0.79	1.61	0.96	1.07	1.89	0.76	0.86	1.70	1.12
WSJ+NYT	SP500 energy	return	-2.23	-2.15	-1.61	-2.37	-2.24	-1.73	-2.16	-2.08	-1.56	-2.18
		variance	1.46	1.69	1.68	1.85	2.12	2.24	1.64	1.85	1.85	1.88
	SP global oil & gas	return	-2.54	-2.39	-0.19	-2.82	-2.55	-1.17	-2.40	-2.28	-1.41	-2.61
		variance	2.86	3.03	331.75	2.91	3.16	6.70	3.08	3.21	47.40	3.54
	SP500 oil & gas	return	0.32	0.47	0.95	0.71	0.06	0.96	-0.48	-1.16	1.51	-0.18
		variance	5.45	4.22	872.17	474.34	0.92	3.48	2.08	6.09	4.72	2.88
	Brown energy	return	-2.65	-2.50	-2.31	-2.07	-1.99	-1.69	-2.69	-2.53	-2.30	-2.50
		variance	0.83	1.04	1.20	1.03	1.25	1.40	0.90	1.11	1.28	1.13
ALL	climate transition	return	-0.50	-2.14	-2.60	-0.35	-0.27	-0.71	-0.37	-0.14	-1.18	-0.85
		variance	-2.71	-65.95	-1.90	-3.68	-4.57	-6.07	-3.43	-7.70	-8.32	-2.58
	Paris-aligned	return	0.14	-0.16	0.05	-0.51	0.20	0.03	-0.58	0.34	-0.23	0.21
		variance	-1.72	-4.93	-3.17	-7.24	-4.70	-3.13	-7.16	-7.89	-2.92	-3.90
	fossil fuel free	return	3.47	3.36	2.54	3.66	3.49	2.72	3.47	3.37	2.55	3.38
		variance	1.89	2.15	1.95	2.71	2.87	2.60	1.95	2.19	1.95	2.22
	ESG	return	-0.45	-0.28	-0.11	-0.62	-0.42	-0.29	-0.33	-0.18	-0.26	-0.32
		variance	-0.26	-0.18	-0.38	0.02	0.14	-0.10	-0.35	-0.26	-2.17	-0.21
WSJ	climate transition	return	-0.62	-0.78	-1.95	-0.90	-1.05	-0.97	-1.07	-0.81	-2.12	-1.59
		variance	-4.37	-4.44	-2.60	-2.05	-2.42	-10.49	-1.90	-5.03	-2.59	-4.16
	Paris-aligned	return	0.06	0.19	-0.09	0.61	0.39	0.55	-0.08	0.22	-0.27	0.32
		variance	-1.26	-1.58	-1.92	-1.64	-4.18	-4.11	-1.37	-2.65	-2.16	-4.08
	fossil fuel free	return	3.94	3.71	2.48	4.05	3.73	2.84	3.88	3.64	2.50	3.68
		variance	2.39	2.39	2.49	2.72	2.68	2.68	2.42	2.41	2.46	2.51
	ESG	return	-0.26	-0.16	0.61	-0.37	-0.30	0.82	0.02	0.06	1.23	-0.34
		variance	-0.83	-0.43	-5.09	-0.49	-0.03	-2.46	-0.96	-0.53	-2.47	-0.76
WSJ+NYT	climate transition	return	-0.52	-0.22	-0.52	-0.21	-0.29	-0.78	-0.26	-0.22	-0.71	-0.35
		variance	-2.73	-5.12	-7.39	-7.94	-5.56	-8.28	-4.97	-5.31	-20.17	-3.93
	Paris-aligned	return	2.13	1.86	2.08	1.33	1.02	2.28	1.37	1.51	0.85	1.14
		variance	-2.86	-5.18	-6.60	-4.21	-3.20	-5.92	-4.20	-3.30	-3.85	-5.28
	fossil fuel free	return	4.07	3.80	3.04	4.15	3.80	3.26	4.13	3.84	3.08	3.90
		variance	2.00	2.07	1.93	2.60	2.62	2.34	2.00	2.06	1.88	2.12
	ESG	return	0.08	0.16	0.37	-0.15	-0.04	0.34	0.30	0.34	0.49	0.23
		variance	-0.28	-0.15	-4.66	-0.11	0.07	-3.93	-0.44	-0.27	-4.78	-0.30

Note: This table gives the z-statistics of the environmental scores in the return and volatility equations (return and variance rows) of the 8 indices. The columns report the results for the 3 environmental scores (buzz, tonality and uncertainty) derived with the 3 weighting schemes (uniform, visibility-focused and relevance-focused) and for the aggregate score (PCA). The top part of the table shows the results for the brown indices and the bottom part those for the green ones. In each block, the results are given for the whole corpus of newspapers (ALL), *The Wall Street Journal* only (WSJ) or *The Wall Street Journal* and *The New York Times* (WSJ+NYT). Red (green) indicates a negative (positive) and significant impact of the score on the returns and a positive (negative) impact on volatility at the 10% level.

Table 3: Estimation results of the augmented CAPM-GARCH model

(a) Brown indices

	SP500 energy		SP global oil & gas		SP500 oil & gas		Brown energy	
	visibility	relevance	visibility	relevance	visibility	relevance	visibility	relevance
α	0.030	-0.084	0.203	-0.158	-0.140	-0.196	0.088	0.002
	(0.81)	(0.35)	(0.24)	(0.23)	(0.45)	(0.15)	(0.46)	(0.98)
β	1.177	1.181	1.324	1.389	1.373	1.347	0.941	0.942
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
δ_1	-0.366	-0.039	-0.597	-0.028	0.012	0.025	-0.291	-0.032
	(0.03)	(0.08)	(0.01)	(0.24)	(0.95)	(0.34)	(0.05)	(0.09)
b_0	-0.079	-0.028	-0.303	-0.209	-0.068	-0.072	0.003	0.015
	(0.26)	(0.54)	(0.02)	(0.00)	(0.54)	(0.00)	(0.97)	(0.78)
b_1	0.062	0.061	0.060	0.003	-0.011	-0.007	0.036	0.033
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)
b_2	0.929	0.930	0.940	1.004	1.012	1.008	0.943	0.948
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
δ_2	0.185	0.021	0.512	0.057	0.123	0.026	0.077	0.010
	(0.03)	(0.03)	(0.00)	(0.00)	(0.36)	(0.00)	(0.21)	(0.16)
R2	0.65	0.65	0.55	0.55	0.47	0.47	0.59	0.59
LB1	0.78	0.83	0.47	0.45	0.76	0.70	0.83	0.81
LB2	0.79	0.85	0.94	0.00	0.29	0.25	0.60	0.64

Notes: This table provides the parameter estimations and the associated p-values in parentheses for the brown indices. The last three lines contain the R-squared of the mean equation and the p-values of Ljung Box tests for autocorrelation of order 12 in the standardized residuals (LB1) and in the squared standardized residuals (LB2).

(b) Green indices

	climate-transition		Paris-aligned		fossil fuel free		ESG	
	visibility	relevance	visibility	relevance	visibility	relevance	visibility	relevance
α	0.024	0.023	0.005	0.013	-0.009	0.003	0.001	0.0001
	(0.16)	(0.03)	(0.86)	(0.48)	(0.30)	(0.64)	(0.86)	(0.99)
β	1.010	1.008	1.026	1.028	1.004	1.004	1.014	1.014
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
δ_1	-0.007	-0.001	0.044	0.008	0.048	0.005	-0.0004	0.0004
	(0.77)	(0.44)	(0.31)	(0.02)	(0.00)	(0.00)	(0.97)	(0.74)
b_0	0.012	0.008	0.027	0.026	0.005	0.006	0.0003	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.43)	(0.04)
b_1	-0.030	0.055	-0.118	-0.123	0.485	0.475	0.085	0.150
	(0.69)	(0.30)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)
b_2	0.482	0.553	0.569	0.507	0.007	0.021	0.859	0.600
	(0.00)	(0.00)	(0.03)	(0.00)	(0.90)	(0.67)	(0.00)	(0.00)
δ_2	-0.009	-0.001	-0.019	-0.003	0.004	0.0005	0.000	-0.0003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.94)	(0.00)
R2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
LB1	0.10	0.18	0.00	0.01	0.99	1.00	0.19	0.11
LB2	0.43	0.30	0.53	0.75	0.88	0.88	0.84	0.55

Notes: This table provides the parameter estimations and the associated p-values in parentheses for the green indices. The last three lines contain the R-squared of the mean equation and the p-values of Ljung Box tests for autocorrelation of order 12 in the standardized residuals (LB1) and in the squared standardized residuals (LB2).

Table 4: Robustness checks

		Robustness 1	Robustness 2									Robustness 3		
	score	PCA	Buzz			Tonality			Uncertainty			uncertainty - alternative weight		
	weight	PCA	uniform	visible	relevant	uniform	visible	relevant	uniform	visible	relevant	uniform	visible	relevant
	dataset	PCA	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT	WSJ+NYT
	weekend	yes	no	no	no	no	no	no	no	no	no	yes	yes	yes
SP500 energy	return	-2.67	-3.40	-3.14	-2.88	-3.72	-3.39	-2.93	-3.26	-3.02	-2.78	-2.00	-1.92	-1.70
	variance	2.00	2.41	2.46	2.24	2.82	2.89	2.74	2.59	2.62	2.39	2.13	2.66	2.62
SP global oil & gas	return	-2.25	-3.67	-3.82	-2.11	-2.98	-3.39	-0.67	-3.15	-3.35	-2.37	-1.50	-1.35	-0.07
	variance	32.12	78.41	74.53	22.75	68.87	68.42	26.33	76.10	72.89	30.63	24.64	24.32	21.02
SP500 oil & gas	return	-0.34	-3.62	-0.51	1.01	0.87	1.41	2.36	-0.23	-0.42	0.31	0.77	0.67	-0.98
	variance	2.81	80.56	5456.40	43.06	7.67	2.39	26.65	3.35	16.60	32.78	4.08	48.38	5.17
Brown energy	return	-2.72	-4.78	-4.28	-4.26	-4.08	-3.67	-3.50	-4.80	-4.29	-4.22	-3.04	-2.77	-2.51
	variance	1.21	1.11	1.17	1.35	1.35	1.41	1.62	1.20	1.26	1.43	1.43	1.74	1.84
climate transition	return	-0.53	0.22	-0.17	-0.39	-0.13	-0.83	-0.39	0.12	-0.22	-0.45	0.05	-0.39	-1.24
	variance	-3.96	-5.49	-22.17	-3.45	-6.52	-2.61	-3.90	-7.65	-215.83	-4.00	-122.24	-3.15	-3.49
Paris-aligned	return	0.48	1.21	1.29	1.74	1.19	1.30	0.66	1.32	2.06	1.92	1.93	1.54	1.53
	variance	-2.55	-12.62	-3.37	-6.41	-2.97	-2.39	-3.14	-2.38	-2.27	-3.15	-3.86	-2.29	-2.10
fossil fuel free	return	3.87	4.58	4.39	3.60	4.59	4.28	3.71	4.63	4.41	3.66	4.58	4.45	3.97
	variance	2.25	1.88	2.03	1.85	2.28	2.42	2.10	1.83	1.96	1.78	1.47	1.39	0.99
ESG	return	-0.14	0.14	0.21	0.58	0.06	0.11	0.83	0.38	0.39	0.74	0.69	0.79	0.57
	variance	-0.42	-0.23	-0.17	-0.29	-0.05	0.01	-4.69	-0.43	-0.34	-0.40	-0.43	-0.12	-1.99

Note: This table gives the z-statistics of the environmental scores in the return and volatility equations (return and variance rows) of the 8 stock indices. The results are reported for the first component of a PCA of the 27 possible scores (column 'robustness 1'), for the 9 scores derived from the NYT and WSJ without articles published on weekends (column 'robustness 2') and for the uncertainty scores with an alternative weight (column 'robustness 3'). Red (green) indicates a negative (positive) and significant impact of the score on the returns and a positive (negative) impact on volatility at the 10% level.

APPENDIX 1 - Sources of the environmental dictionary

Lexicons provided by organisations

- EPA http://www.epa.ie/footer/a-zglossaryofenvironmentalterms/
- European Environment Agency https://www.eea.europa.eu/help/glossary
- Intergovernmental Panel on Climate Change (IPCC) https://www.ipcc.ch/sr15/chapter/glossary/
- United Nations https://unfccc.int/process-and-meetings/the-convention/glossary-of-climate-change-acronyms-and-terms

Thesaurus on environmental issues

- Cambrige https://dictionary.cambridge.org/topics/the-earth-and-outer-space/environmental-issues/
- General Multilingual Environmental Thesaurus https://www.eionet.europa.eu/gemet/en/themes/
- MacMillan https://www.macmillandictionary.com/thesaurus-category/british/environmental-issues
- Wall Street English https://wallstreetenglish.fr/fiches-anglais/carriere/vocabulaire-environnement-ecologie-en-anglais
- BabelCoach http://www.babelcoach.net/fr/vocabulaire_anglais/vocabulaire_environnement_ecologie_avance

Glossaries provided by online encyclopaedia

- Ballotpedia https://ballotpedia.org/Glossary_of_environmental_terms
- Wikipedia https://en.wikipedia.org/wiki/Glossary_of_ecology

Glossaries provides by newspapers on climate change

- The BBC https://www.bbc.com/news/science-environment-11833685
- The Guardian https://www.theguardian.com/environment/2009/sep/22/climate-change-glossary-jargon
- The NYT https://www.nytimes.com/1997/12/01/world/global-warming-a-climate-change-glossary.html

Glossaries provided by research centres and universities

- Grains Research and Development Corporation in Australia (GRDC) https://www.gdrc.org/uem/ait-terms.html
- Auburn University https://cla.auburn.edu/ces/glossary/
- Boston University http://www.bu.edu/sustainability/reference/glossary-of-terms/
- University of California Davis https://climatechange.ucdavis.edu/science/climate-change-definitions/
- Harvard University https://research.gsd.harvard.edu/zofnass/glossary/
- Michigan State University https://ehs.msu.edu/enviro/whpp/wh-17glossary.html
- University of Miami http://climate.miami.edu/glossary-of-terms/

APPENDIX 2 - Environmental lexicon

1.5 degree, abandoned well, acid precipit, acid rain, aerosol, air conditioning, air quality, air temperature, air toxic, algae, algal, alternative energ, animal protect, animal wast, anthropogen, anti consumerist, aquifer, asbestos, backyard burn, beach cleansing, ber , biochar, biodegrad, biodiesel, biodivers, bioenerg, bioethic, bio fuel, biofuel, biogas, biohazard, biological agent, biological control, biological reserv, biosphere reserv, biomass, biome , biotic, bird sanctuar, black bin, black tide, brown bin, bye law, cadmium, cap and trade, carbon , carbons , carbonic acid gas, carbonis, carboniz, carcinogen, car pool, carpool, catalytic conver, cfc, cfl bulbs, chemical wast, civic amenity site, clean air, clean coal, clean develop, clean energ, clean power, clean water, climate adapt, climate alterat, climate change, climate damage, climate effect, climate event, climate extrem, climate feedback, climate forc, climate gov, climate justice, climate migra, climate mitigat, climate model, climate neutral, climate project, climate protect, climate refugee, climate regulat, climate resilien, climate response, climate sensitiv, climate system, climate target, climate varia, climatolog, co2, coast protect, coastal erosion, coastal manag, coastal protect, coastal restorat, compost, conference of the parties, conservancy, conservation, consumer wast, contamina, crop spray, cryptosporidium, cumulative emission, cyclone, decarbur, decoke, defolia, deforest, desertification, detrit, digester, dioxin, disafforest, disforest, dispersant, dog day, domestic wast, draught proofing, drift ice, eco , ecocide, ecocit, ecodevelop, ecolabel, ecolog, ecotecture, ecoterrorist, ecotouris, ecotown, effluent, electric car, electric moto, electric truck, electric vehicle, el nino , emission allow, emission control, emission inventor, emission level, emission limit, emission project, emission reduc, emission scenari, emission standard, emission trad, emission trajector, emissions allow, emissions control, emissions inventor, emissions level, emissions limit, emissions project, emissions reduc, emissions regist, emissions scenari, emissions source, emissions standard, emissions trad, emissions trajector, endangered animal, endangered area, endangered bird, endangered fish, endangered plant, endangered species, energy efficien, energy rating, energy sav, energy star, energy waste, engine emi, environment damage, environment friendly, environment protect, environmental, erosion control, eutrophication, exhaust filter, exhaust fume, exhaust gas, extinct species, extreme temperature, extreme weather, fauna, feed in tariff, fertilis, fertiliz, fish kill, fishing preserv, fishing reserv, flood area, flood plain, flood prevent, flood protect, flora restorat, fly ash, food securit, food wast, forest degrad, forest damag, forest destr, forest manag, forest polic, forest preserv, forest protect, forest reserv, forest resource, forest restorat, fossil energ, fossil fuel, frack, freecycle, fuel efficien, fuel povert, garbage, gas emi, geoengineer, geothermal electr, geothermal energ, geothermal gener, geothermal heat, geothermal industr, geothermal invest, geothermal plant, geothermal power, geothermal project, geothermal sourc, geothermal well, ghg, glacial retreat, glacier, global climate, global temperature, global warming, gray water, green act, green agenda, green alternativ, green asset, green audit, green bank, green behav, green belt, green bin, green bond, green build, green business, green car, green certif, green cit, green climate fund, green compan, green consum, green constr, green corridor, green credential, green credit, green deal, green design, green develop, green diesel, green econom, green electr, green energ, green farm, green fee, green financ, green firm, green fuel, green fund, green group, green grow, green home, green hous, green ind, green infrastructure, green inves, green job, green image, green initiative, green innovat, green label, green leader, green legislat, green loan, green lobb, green measure, green mov, green new deal, green oppo, green part, green plan, green polic, green power, green product, green program, green project, green purchas, green regulat, green residen, green revolution, green roof, green shop, green solution, green source, green space, green stock, green subsid, green tax, green tech, green tide, green touris, green town, green trad, green transport, green vehicle, green wash, greenwash, green work, greener, greenhouse, greenly, greenness, greens , greentailing, grey bin, greyfields, grey water, ground cover, ground water, groundwater, habitat damage, habitat destr, habitat fragment, habitat loss, habitat preserv, habitat restorat, hazardous air, hazardous chemical, hazardous liquid, hazardous material, hazardous metal, hazardous shipment, hazardous substance, hazardous wast, heat island, heat wave, heatwave, household wast, hurricane, hydraulic power, hydrologic cycle, hydrological cycle, iceberg, icecap, ice loss, ice sheet, ice shelf, incinerat, industrial emi, industrial fume, industrial sludge, industrial wast, invasive species, keystone species, kyoto accord, kyoto agreement, kyoto protocol, kyoto treat, la nina, land damage, land degrad, land erosion, land planning, land preserv, land protect, land restorat, land subsidence, land use, landfill, landscape damage, landscape protect, landscape restorat, leachate, lead level, lead poison, leed , liner material, litter bin, litterbug, localvore, low energ, manure management, marine ecosystem, marine protect, marine reserve, marine snow, mbt , meteorological disaster, meteorological phenomenon, methane, modified organism, monitoring station, monsoon, mountain protect, mudslide, municipal wast, mutagen, natural area, natural disaster, natural park, natural reserve, natural resource, natural variabilit, nature preserv, nature protect, nature reserve, negative emission, niche construct, nitrate, nitrogen cycle, nitrogen oxide, nitrous oxide, non poisonous, nonpoisonous, non toxic, nontoxic, nox , noxious air, noxious cloud, noxious diesel, noxious dust, noxious emi, noxious gas, noxious haze, noxious nutrient, noxious smell, npws, nss, nuclear accident, nuclear disaster, nuclear fallout, nuclear issue, nuclear risk, nuclear safety, nuclear wast, nuclear winter, nutrient remov, ocean acidif, off grid, off the grid, oil residu, oil slick, oil spill, oilspill, organic, organophosphate, overgraz, overpopulat, ozon, pack ice, paris agreement, particulate, pay by weight, peak emission, peak oil, pcb, permafrost, pest , pesticid, photovoltaic, plankton, planning permission, plant protect, plastic bag, point source, poison cloud, pollinat, pollut, preservationist, protected area, protected bird, protected forest, protected land, protected marine, protected species, radiative forcing, radioactiv, radon , rain forest, rainforest, rainwater harvest, rare species, reafforest, re afforest, reclaimab, recycl, reforest, refuse dump, renewab, reprocess, resource damage, resource depletion, resource efficien, resource preserv, resource protect, resource reserve, resource scarc, resource use, resource utiliz, resources damage, resources depletion, resources efficien, resources preserv, resources protect, resources reserve, resources scarc, resources utiliz, reusab, reuse, revegetation, reverse osmosis, rewilding, risk species, river basin, salinat, saliniz, sanitation plan, scrap yard, scrapyard, scrub , sea ice, sea level, season creep, seepage, sensitive area, septic tank, sewage, sewer system, sewer water, sewerage system, site protect, site rehabilit, slow cit, smog, smokeless fuel, soil acidificat, soil erosion, soil moisture, soil protect, soil qualit, solar array, solar batter, solar cell, solar compan, solar cycle, solar electr, solar energ, solar farm, solar gener, solar industr, solar invest, solar manuf, solar panel, solar plant, solar power, solar project, solar radiation, solar sourc, solar stock, solid particle, solid wast, soot , species diversit, species extinct, species protect, species reintrod, spillage, sssi, state park, storm water, stormwater, superfund , surface temperature, surface water, sustainable agricultur, sustainable animal, sustainable architect, sustainable build, sustainable cit, sustainable construct, sustainable consum, sustainable cult, sustainable development, sustainable durab, sustainable dwelling, sustainable energ, sustainable farm, sustainable fish, sustainable food, sustainable forest, sustainable fuel, sustainable garden, sustainable industr, sustainable infrastructure, sustainable land, sustainable living, sustainable management, sustainable material, sustainable mobil, sustainable planet, sustainable practice, sustainable produc, sustainable resource, sustainable shopping, sustainable society, sustainable source, sustainable transport, sustainable touris, sustainable urban, sustainable use, sustainable utiliz, sustainable water, throwaway, tidal electr, tidal energy, tidal power, tidy town, tornado, toxic chemical, toxic cloud, toxic dust, toxic emi, toxic fume, toxic gas, toxic substance, toxic wast, toxin, threatened species, tradeable permit, traffic calming, traffic emi, traffic noise, trash, tree hugger, tropospher, tsunami, typhoon, umbrella species, underground stor, unleaded, upcycl, uptake, u valu, vanishing species, vanished species, vehicle emission, vulnerable species, warmer homes scheme, warming ocean, waste avoid, waste disposal, waste dump, waste export, waste gas, waste heat, waste limit, waste import, waste manag, waste minim, waste prevent, waste recover, waste reduc, waste removal, waste stor, waste stream, waste treatment, waste water, wastewater, water column, water cycle, water damage, water efficienc, water manag, water monitor, water polic, water protect, water quality, water resource, water sav, water scarc, water shortage, water stress, water use, wave energ, wave power, weather modif, weed killer, weedkiller, well water, wetland, wildfire, wind electr, wind energ, wind farm, wind gener, wind industr, wind plant, wind power, wind project, wind sourc, wind stock, wind tower, wind turbine, zero emi, earth system governance project, esgp, fridays for future school strike for climate, gggi, ipcc, iucn, united nations environment program, unep, european environment agency, pemsea, eia , epa , bureau of land management, blm , national park service, itec , greenpeace, cerc , earth island institute, nature friends international, global footprint network, nrdc, unfccc, weee, wildlife, world agroforestry centre, worldwatch institute, wwf.