Firm-specific Climate Risk Estimated from Public News

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Abstract

We estimate firm-specific exposures to climate risk from public news covering a period of 20 years by applying a novel topic modeling algorithm. We differentiate between regulatory (or transition) and physical climate risks and document that financial markets price both risks. Our study is the first to find a positive and statistically significant risk premium for physical climate risk. For regulatory climate risk we find a regime shift occurring around the year 2012 reconciling the conflicting evidence in the literature. While the risk premium is positive in the earlier period, it becomes significantly negative in the later one. A long-short portfolio that is long "green" firms and short "brown" firms, as identified by their topic exposures in public news, constitutes a priced risk factor and shows a surprisingly strong correlation with an ESG-sorted benchmark portfolio.

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1 Introduction

Do share prices reflect firms' exposures to regulatory and physical climate risk? The literature on ESG (Environmental, Social, and Governance) related asset pricing is growing very fast.[1] While most research tries to construct risk measures from a vast amount of data on the corporate climate footprint, we take a different route and deduct firms' risk exposures to climate risk from news.

Specifically, we use news released via the Thomson Reuters newswire during the last 20 years. In contrast to the common approach in academia as well as industry to use climate-related ESG-scores or emission data as proxies for climate risk exposures, our machine-learning approach assigns firm-specific news texts to climate-related topics, and hence, is able to compute firm-specific measures of exposures to climate risk. Desirable features of using news are its high frequency, that it can be observed in real time, and that it covers a long history, as news archives start in the 1990s while other climate risk related databases have become available only during the 2010s. News also offers two important advantages content-wise. First, any aspect of a given topic that is potentially relevant for the readers of a news outlet will be covered by news. Thus, extracting information from news has the potential to capture the relevant aspects of a given topic in a very comprehensive manner. Second, news in many cases will also capture forward-looking aspects of the discussed problem and will not only rely on a backward-looking perspective.

However, those benefits of news come with a big disadvantage: text data is unstructured and high-dimensional (Gentzkow et al., 2019), which is why it has to be transformed into a machine-readable form first. This involves additional challenges, such as sizable computational costs, difficulty in identifying and extracting useful information, or the lack of labels to train a machine-learning model. In this study, we apply a novel method which is fast, flexible and transparent. It also represents an unsupervised learning approach and, thus, does not require any labeled training dataset.

Specifically, we propose Guided Topic Modeling (GTM), an algorithm to generate

[1] We provide a literature review in Section 2.

weighted lists of unigrams and bigrams, i.e., individual words and 2-word phrases, that are most representative for a particular topic. The only information required are two (or more) seed words that describe a topic. These seed words are then mapped to word embeddings via a self-trained Word2Vec model.[2] Word embeddings represent high-dimensional vector representations that can be used to identify similar words in the multidimensional space using vector algebra and different mathematical concepts of distance.

The algorithm, however, does not simply collect words closest to the seed words. It also learns about the topics' representation from the data and determines the optimal topic center in the vector space. In the end, the algorithm yields a similarity parameter (weight) for each unigram and bigram that is higher for words closer to the topic center (i.e., words that are highly representative of a topic) and lower for words that are more distant form the topic center (i.e., less important words).

While the proposed GTM algorithm can be used in any context, we specifically use it to identify words that cover different topics related to climate risks and opportunities, specifically, (i) regulatory climate risk (or transition risk), (ii) physical climate risk and (iii) sustainability (the idea of this third group of topics is to capture opportunities in the context of sustainability). Once we have the topic word lists, we calculate the exposure of 4.95 million news articles to each climate-risk related topic. As news articles are tagged with metadata that include the associated companies, we are able to match news articles to individual firms. Next, we calculate company-specific topic exposures as the topic-weighted sum of words in all news articles related to a specific company. In principle, we observe this measure at the daily frequency. However, not every firm is covered in the news every day and, thus, we smooth these firm specific exposures over a rolling window of two years in our main results.

To evaluate the economic plausibility of the estimated exposures, we first analyze industry distributions of firms that are exposed to regulatory and physical climate risks. We find that (i) *Electric, Gas, and Sanitary Services*, (ii) *Coal Mining* and (iii)

[2]see, Dangl and Salbrechter (2023). Word2Vec is a machine learning algorithm used to represent words as vectors in a high-dimensional space, while capturing semantic relationships between them (Mikolov et al., 2013).

Petroleum Refining and Related Industries have the highest exposures to regulatory climate risk during the sample period. For physical climate risk, we find that *Electric, Gas, and Sanitary Services* has the highest exposure followed by *Insurance Carriers. Oil and Gas Extraction* and *Food and Related Products* have the third and fourth highest exposure. In both cases, these industry exposures appear to be economically sensible suggesting that the news-based approach picks up relevant information about firm-specific climate risk exposures.

Equipped with these firm-level news-based exposures, we then assess whether regulatory and physical climate risks are priced in equity markets. Using Fama-MacBeth regressions, in which we control for CAPM betas, market capitalization, book-to-market ratios, operating profitability, and investment, we find a statistically significant positive risk premium of 1.5% p.a. for physical climate risk. The risk premium is robust to the inclusion of sector or industry fixed effects and, thus, captures an effect that is tied to the individual firm. This result is particularly noteworthy, as our study is the first which explicitly documents that physical climate risk is priced in equity markets.

Looking at regulatory climate risk, we find a more nuanced picture. Over the full sample period, the estimated risk premium is small and statistically insignificant. This result, however, is due to a regime shift in the risk premium occurring around 2012. If we split the sample roughly in half, we find a positive and statistically significant risk premium of 1.54% p.a. during the earlier years. Such a positive risk premium is consistent with the idea that stocks exposed to regulatory climate risk are riskier in financial terms (see, for example, Bolton and Kacperczyk, 2021; Hsu et al., 2022). During the latter years, however, the risk premium switches sign and becomes significantly negative with a point estimate of -2.56% p.a. While a negative risk premium seems counter-intuitive, it has been rationalized through large increases in the demand for green assets (see, for example, Pástor et al., 2022). In fact, this regime shift in the risk premium of regulatory climate risk that we are able to document within a consistent framework due to the substantially longer time-series of data, provides an explanation for the ongoing controversy in the literature about the returns of green and brown investments and about the sign of the regulatory climate risk premium.

A disadvantage of relying on news coverage is that the sample of firms that are covered in the news is substantially smaller than the universe of listed equities in the US. Thus, we expand the empirical analysis to all stocks in a next step. To do this, we first create a *green-minus-brown* portfolio (GMB portfolio) that is long firms with high exposures to sustainability (i.e., a portfolio of firms offering opportunities in terms of sustainability) and short firms that show high exposures to regulatory climate risk. Constructing the long-short portfolio in this way has the important advantage, compared to the literature, that green firms are explicitly identified as firms with sustainability-related opportunities instead of being just classified as firms with no or little exposure to climate risk.[3] We then add the monthly returns of this long-short strategy to the market model and calculate climate betas for each stock using rolling-window time-series regressions. The obtained climate betas capture exposures to regulatory climate risk in an inverse way — high betas indicate green firms with low exposures, while low betas indicate brown firms with high exposures.

In the case of physical climate-risk betas, we need to follow a slightly different approach, as in this case we do not have a way to directly identify those firms with low exposures to physical risks. As a consequence, we construct a long-short portfolio by going long in firms with high exposures to physical risks and shorting all other stocks. Then we, again, calculate physical climate-risk betas for the universe of stocks, as described above.[4]

Given these approaches, we calculate regulatory climate-risk betas and physical climate-risk betas for a total of around 9000 firms over the period Jan. 31, 2002 to Dec. 31, 2020. Using these betas, we confirm the results from news-based exposures described above: We observe downward sloping cumulative returns of the GMB portfolio from 2002 to 2012 followed by strong positive returns until 2020. This outperformance from 2012 onwards cannot be explained by classic risk factors as we obtain an alpha of 9.60% p.a. when regressing the GMB portfolio on the Fama-French 5-factor model

[3]This aspect is related to the broader issue of whether no information is good or bad. See, for example, Engle et al. (2020) who classify days with no news about climate risk as low-risk days.

[4]To validate the regulatory- and physical climate-risk betas, we also build portfolios and construct long-short strategies. Comparing the returns of these beta-based portfolio sorts to the returns of news-exposure-based sorts yields correlations of 0.6 and higher for monthly and quarterly returns.

plus momentum. We further show that extending factor models by the climate risk factors, i.e., the GMB- and the high-minus-low physical climate-risk portfolio, significantly improves the explainability of asset return variations, as reflected in reductions of the GRS (Gibbons et al., 1989) test statistic.

A final, noteworthy result is that the monthly returns of our climate-beta based GMB portfolio and the returns of the GMB portfolio of Pástor et al. (2022), which is constructed in a completely different way using ESG data from MSCI, show a surprisingly large correlation of 0.64. This provides external validation of our approach, as it shows that we are able to extract climate-related information that is comparable to the one captured by E-related MSCI scores, but exclusively from news.

The remainder of this paper is structured as follows: In Section 2 we provide a review of the related literature, in Section 3.1 we describe the data and in Section 3 we give a detailed description of our methodology. This includes the topic modeling algorithm (Section 3.2), a visualization of the obtained topics (Section 3.3) as well as a description of all necessary steps to obtain company specific news indices (Section 3.4). Thereafter we present the results (Section 4), starting by highlighting the firm- and industry-specific topic exposures, which we use in Section 4.2 to form climate risk portfolios. In Section 4.3 we present the results of the Fama-MacBeth cross-sectional regressions and in Section 4.4 we calculate climate risk beta coefficients which we use to form beta-sorted climate risk portfolios. In Section 4.5, we validate our results by first showing the correlation with an ESG-sorted benchmark portfolio (Section 4.5.1) and second by calculating the exposure to well-known risk factors (Section 4.5.2). Thereafter, we present factor model extensions by including our climate risk factors (Section 4.5.3) and lastly show in Section 4.5.4 that climate betas predict future news flows.

2 Related Literature

This paper relates to a quickly growing literature that evaluates different ways to learn about the climate-risk exposures of firms and examines whether climate risks are priced-in in equity markets. Related studies frequently rely on traditional data sources to measure individual firms' climate-risk exposures such as ESG data (Engle et al., 2020; Pástor et al., 2022; Seltzer et al., 2022) or emissions data (Ardia et al., 2020; Bolton and Kacperczyk, 2021; Hsu et al., 2022). Engle et al. (2020) use ESG data from Sustainalytics and MSCI to measure individual firms' exposures to climate risks. By implementing a mimicking-portfolio strategy, the authors attempt to dynamically hedge climate-change risk as measured by innovations of a climate-news series that is extracted from the Wall Street Journal news feed. Bolton and Kacperczyk (2021) report a positive, statistically significant, transition-risk premium for high-emission firms using firm-level emissions data from Trucost covering 77 countries and 14,400 firms from 2005 to 2018. The risk premium is more pronounced when controlling for industry fixed effects, suggesting that industries with high emission levels have earned low returns.

Similarly, we also observe an increase in transition risk from 1.54% p.a. (t-value: 1.61) to 1.75% p.a. (t-value: 2.34) after controlling for industry fixed effects over the period 2002 to 2012 (see the Fama-MacBeth regressions in Table 7). For the period 2012 to 2020 in contrast, we observe a risk premium that is negative, but insignificant. Also, Bolton and Kacperczyk (2021) observe no statistically significant transition-risk premium associated with emission levels for North America over the shorter period from 2014 to 2017 – the two years before and after the 2015 Paris climate agreement – while Asia experienced a sharp increase in the risk premium for the two years following the conference.

Furthermore, Seltzer et al. (2022) documents that US firms with poor environmental profiles, as measured by their ESG rating, as well as high carbon emission firms, as measured by data from the Carbon Disclosure Project (CDP), are associated with lower credit ratings and higher yield spreads. The authors further find that this effect is amplified for firms located in states with stricter enforcement of regulations, i.e., firms that are more likely affected by regulations. Choi et al. (2020) documents a climate related attention effect – people update their beliefs about climate change when they are personally exposed to warmer-than-usual temperatures. As a consequence carbon-intensive firms underperform relative to low-carbon-emitting firms on these days.

Traditional data sources usually have the disadvantages of being backward looking, time-lagging as they are only available at low frequencies and limited in historical coverage since the reporting of emission data became only mandatory with the signing of the Mandatory Reporting of Greenhouse Gases Rule of the Environmental Protection Agency in 2010. One alternative way to gather valuable climate information is text data in the form of earnings-call transcripts or news data.

Sautner et al. (2023a) applies a keyword discovery algorithm to generate lists of climate related keywords from a short list of initial keywords that describe different climate topics, namely *climate-change opportunity*, *physical* and *regulatory climate risk*. They use earnings-call transcript data to measure the individual firm's climate risk exposures by counting the overlapping words between transcripts and climate topics. By conducting a variance analysis, the authors find large firm-level variations in exposure measures, i.e., variations also exist among firms within the same industry. Furthermore, the authors provide evidence that climate exposures are priced in the options and equity markets. A conditional factor constructed from innovations in climate-change exposures is positively correlated with higher uncertainty and thus, higher returns.[5]

In a follow-up study, Sautner et al. (2023b) test whether climate risks are priced in the cross-section of S&P500 firms. By performing a Fama-MacBeth regression over the period Jan. 2008 to Dec. 2020 the authors find an insignificant risk premium for *climate-change opportunity*, *regulatory* and *physical climate risks*. Only when using proxies for expected returns do the risk premia for *climate-change opportunity* and *regulatory climate risk* become significant; however, at low margins with risk premia being below 0.23% p.a. Furthermore, the authors find weak support of topic exposures in the earnings-call transcript data before 2008 which is why they exclude earlier years. In particular, the exposure to *physical climate risk* is close to zero in the vast part of their sample, leading to insufficient variation in the variable which in turn results in an ill-defined estimation problem. Therefore, the authors do not find a risk premium for physical climate risk.

In contrast, our financial news dataset is not affected by such limitations. With almost 5 million news articles, we find sufficient support for all climate topics in the

[5] In addition, the authors show that climate change exposure predicts job creation in green technologies as well as green patents.

data from January 2002 onwards. In contrast to Sautner et al. (2023b), we also study a much larger sample of firms and develop our own guided topic modeling approach to extract relevant, firm-specific information from the news. Given this setup, we find starkly different results, as we document a significantly positive risk premium for physical climate risk, and a time-varying risk premium for regulatory climate risk.

Another strand of the literature extracts climate-risk related information from 10-K reports. Kölbel et al. (2020) classify climate related texts in these reports into the categories transition and physical climate risk by using a fine-tuned BERT model named ClimateBERT and analyze how mandatory regulatory disclosures affect the CDS term structure. The authors document opposing effects of disclosing transition and physical risks: when transition risks are disclosed, the CDS spreads tend to increase, due to increased uncertainty, while when physical climate risks are disclosed, they tend to decrease due to reduced uncertainty. Similarly, Berkman et al. (2021) utilize a firm-specific measure of climate risk based on 10-K reports and find that increased climate risk reduces firms' valuations. The authors report a negative impact on the prices of firms with high climate risk when investor attention to climate risk, triggered by catastrophic events such as floods or hurricanes, is high.

3 Empirical Methodology

In contrast to papers that use environmental scores from ESG data providers as a measure of firms' sustainability (see, e.g., Pástor et al., 2022, who rank firms along the environmental (E) score obtained from MSCI ESG data), or studies that utilize emissions data (see, e.g., Bolton and Kacperczyk, 2021; Hsu et al., 2022), we approach this problem from an entirely different angle. We deduct a firm's exposure to various types of climate risk from its presence in related news articles. In this section, we will first describe the news and return data we use. We will then outline in detail the machine-learning framework developed to extract information from the news.

3.1 Data and Data Preprocessing

This research paper is based on a comprehensive dataset of news articles published via the news agency Thomson Reuters. It contains over 40 million news items, each linked to metadata with exact timestamps of publication, topic- and geography codes as well as ticker codes for firm-related news. The dataset covers the period from January 1996 to July 2021. We restrict our analysis to news written in English language, which sum up to a total of 12.42 million articles as well as to U.S. news, i.e., news tagged with the U.S. geography code, which finally results in a dataset of 4.95 million news articles.

In a next step we clean the raw news data by excluding author information such as phone numbers, email addresses and URLs. We transform the text to lowercase and remove numbers, parentheses, and additional information added by Thomson Reuters such as notes and keywords. Also, we form multi-word expressions (bigrams) by training and applying the Phrases model available in the Gensim Python package, (see Řehůřek and Sojka, 2010).

Furthermore, we collect security data from CRSP and select all stocks with share codes 10 and 11. Since small firms, as measured by their market capitalization, have only a minor news exposure, we exclude firms with a market capitalization below the median market capitalization across all CRSP stocks in each month for the main news-based analysis. Later, in Section 4.4 we relax this restriction and include all stocks with a market cap above 5 million in each month.

3.2 Guided Topic Modeling

Keyword matching is a simple, unsupervised classification technique that does not require the training of a model. By counting the occurrences of selected words describing a topic in a text document, an exposure metric is obtained that explains how strongly the selected topic is represented in the text. Studies that apply such an approach include Ardia et al. (2020); Baker et al. (2016); Engle et al. (2020); Sautner et al. (2023a) among others. The main challenge thereby is to determine lists of words (consisting of uni- or bigrams) that are most representative of describing certain topics. Authors often rely on pre-specified dictionaries (Baker et al., 2016) as the manual creation of comprehensive lists of representative words is considered a "near-impossible" task for humans (Hayes and Weinstein, 1990). King et al. (2017) argue that the human brain has limited abilities to recall keywords, which prevents us from manually creating comprehensive, unbiased word lists. To circumvent a manual generation of word lists, Sautner et al. (2023a) rely on a keyword discovery algorithm developed by King et al. (2017).

We, in contrast, apply a novel approach that we label *Guided Topic Modeling with Word2Vec (GTM)* (see Dangl and Salbrechter, 2023) which enables us to efficiently generate comprehensive topic clusters. One unique aspect of GTM is that each word (i.e., a unigram or bigram in our specific implementation) is associated with a weight parameter. Words that are closer to the center of a given topic in a multidimensional vector space receive a higher weight than more distant words that are less representative.

Guided Topic Modeling is based on vector representations of words (word embeddings) which we obtain from a Word2Vec model, (see Mikolov et al., 2013). We pretrain the model on a total of 10 million news articles (2.5 billion words) of the Thomson Reuters news dataset, covering the period from January 1996 to December 2017.[6]

The Word2Vec model translates words into dense vector representations that capture semantic similarities between words. Words that appear in similar contexts tend to have similar meanings and thus, receive embeddings that point in similar directions in the embedding space. To avoid data sparsity we train Word2Vec with a rather low embedding dimension of n=64. The quality of topic identification is determined by our clustering algorithm and the Word2Vec hyperparameters, especially the embedding size, the Word2Vec algorithm (CBOW is preferred over skip-gram) and the window size. Choosing a too high embedding size or a too narrow window will result in topic-word clusters that are too specific and do not generalize well. Also, we augment the obtained word embeddings with information about word polarity and transform all embedding vectors to unit length.

With the word embeddings at hand we perform topic clustering in the embedding space. However, in contrast to Angelov (2020); Grootendorst (2022); Sia et al. (2020)

[6]We do not limit the training data to news with the U.S. geographic code, but use all English news.

we do not run a clustering algorithm that detects a certain number of latent topic clusters (densely populated areas) in the embedding space. Instead, we generate topics based on seed words. With this approach, we are able to generate an unlimited number of topic clusters without being limited to the output of a clustering algorithm that has no guarantee that a topic of interest will actually be identified as a latent topic.

The algorithm takes as input a list of two or more seed words, each associated with a weight parameter. The vectors representing the seed words span an initial plane (subspace) in the embedding space. All word vectors contained in the embedding space are projected on the plane (subspace) and the word with the smallest projection angle, i.e., the word that is closest to the plane, is added to the topic cluster. Thereafter, the location of the plane is adjusted to minimize the residual sum of squares to all topic vectors. Thus, the topic center is not defined by the seed words but the algorithm iteratively finds an optimal topic center (i.e. the final orientation of the plane).

Next all remaining word vectors are projected on the adjusted plane and the procedure continues until a certain cluster size is reached. After the topic generation is finished, we project all topic vectors on the final plane to calculate the weights of the topic words. The weight is calculated by the Frobenius norm of the two projection coefficients. Thus, the weight would be 1 if a vector lies in the plane and 0 if it is orthogonal to the plane. Consequently, words located closer to the topic center (final location of the plane) receive larger weights than more distant words.

In addition, the parameters and hyperparameters of the clustering algorithm allow to control the characteristics of the generated topic clusters. The weight associated with each seed word controls the location of the topic center relative to each word. The topic center will be closer to seed words with larger weights than to seed words with lower weights. In addition, negative seed words can be defined to avoid unwanted terms in the topic cluster. Finally, a gravity parameter can be used to drag the topic center closer to the location defined by the initial seed words. For a detailed description of the clustering algorithm we refer to Dangl and Salbrechter (2023).

With the obtained topic word lists we perform weighted keyword matching over all 4.95 million news articles. We count the number of words in each article that overlap with the words contained in a topic list and then multiply the count by the associated weights. The sum of these weighted word counts gives us a score (loading) that indicates how strongly a topic is related to a given news article. To make the topic loadings comparable across news articles and topics, we adjust the loadings for differences in news article lengths and word frequencies.

Finally, we generate company-specific topic indices by selecting all news articles related to a firm of interest and aggregating the loadings from individual news to daily scores. We then use the information reflected in the company-specific topic indices to identify green and brown firms as well as firms exposed to physical climate risks, as described in the following sections.

3.3 Topics

We use GTM to generate subtopics that capture aspects of the three themes that we focus on in this study: regulatory climate risk, physical climate risk, and sustainability. Regulatory climate risk, often denoted as transition risk, emerges from new laws and regulations that could harm companies' profits due to mandatory investments in greener production facilities or due to penalty payments like carbon taxes. Physical climate risk is the risk of destruction of firms' assets (production facilities, real estate, farmland, assets) due to extreme weather events, floods, droughts or hurricanes. Sustainability captures green technologies and key concepts that define environmentally friendly businesses.

Each of the three main topics is captured via several subtopics – four subtopics for regulatory climate risk and sustainability and eight subtopics for physical climate risk – which are shown in Figure 1. The weight of each word in a topic is visualized by the font size, i.e., words closer to the topic center appear larger, more distant words appear smaller. The seed words used in GTM to generate these topics are shown in Table 1.

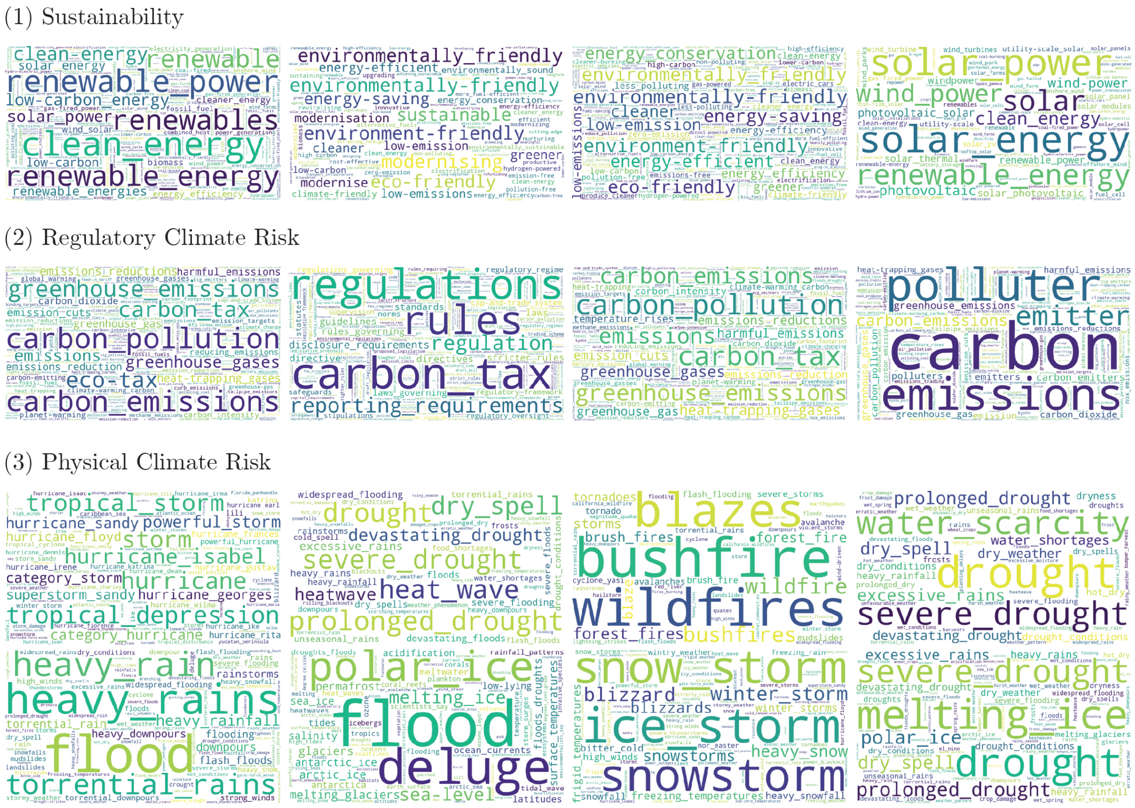


Figure 1: Subtopics generated with GTM and the seed words shown in Table 1. The font size of the words indicate the distance of each word to the topic center. Words close to the center appear large, more distant words are smaller.

	Positive Seed Words (Weight)			Negative Seed Words (Weight)	
(1) Sustainability					
Subtopic 1	renewable_energy (1.0)	clean_energy (1.0)		fossil_fuel (-0.2)	
Subtopic 2	environmentally_friendly (1.0)	sustainable (1.0)	modernising (1.0)	car (-0.5)	carbon (-0.5)
Subtopic 3	environmentally_friendly (1.0)	eco-friendly (1.0)		burning (-0.5)	
Subtopic 4	solar_power (1.0)	wind_power (1.0)		fossil_fuel (-0.4)	
(2) Regulatory Climate Risk (Transition Risk)					
Subtopic 1	eco-tax (1.0)	carbon_tax (1.0)			
Subtopic 2	regulation (1.0)	carbon_tax (1.0)			
Subtopic 3	carbon_pollution (1.0)	carbon_tax (1.0)			
Subtopic 4	polluter (1.0)	carbon (1.0)	emissions (1.0)	emissions_reduction (-0.2)	
(3) Physical Climate Risk					
Subtopic 1	storm (1.0)	hurricane (1.0)			
Subtopic 2	heat_wave (1.0)	drought (1.0)		cold_weather (-0.5)	
Subtopic 3	wildfires (1.0)	bushfire (1.0)		cold_weather (-0.5)	fires (-0.5)
Subtopic 4	water_scarcity (1.0)	drought (1.0)		heavy_rains (-0.5)	epidemic (-0.5)
Subtopic 5	flood (1.0)	heavy_rain (1.0)			
Subtopic 6	sea-level (1.0)	flood (1.0)			
Subtopic 7	blizzard (1.0)	ice_storm (1.0)		hurricane (-0.5)	hot_weather (-0.5)
Subtopic 8	melting_ice (1.0)	drought (1.0)			

Table 1: Seed words used in GTM to generate subtopics. The GTM algorithm takes as input a list of two or more seed word with positive weight. To further guide the topic in a desired direction, we also define negative seed words if needed.

3.4 News-Based Topic Indices

We calculate the coverage of these subtopics in individual news articles by counting the number of words in each article that overlap with the words contained in a topic. These counts are then multiplied by the weights, i.e., the importance of the words. We limit the count, i.e., the contribution of a single word in a subtopic, to a maximum value of 4 to avoid a high score driven exclusively by one or a few words. The sum of these weighted word counts finally provides us with a score (loading) that indicates how strongly a topic is represented in a given news article. As each main topic is comprised of multiple subtopics, we calculate the final topic loading of a given news article as the mean of the individual subtopic loadings.

3.4.1 Scaling of the News-Based Topic Indices

The different news indices have different magnitudes as the words assigned to each topic occur with different frequencies in the text corpus. Topics composed of words that occur more frequently tend to have higher news exposures and thus higher values on average than topics containing less frequent words. In addition, news articles with a high word count, as opposed to short news articles, would receive a disproportionate topic loading, overstating the relevance of long news articles.

To make the topic indices comparable, we adjust the topic loading of each news article with two adjustment parameters, g_{freq} and g_{len}. To calculate g_{freq}, we first count how often each word w_i appears in the corpus (c_i) and then calculate the average count $\bar{c}$ over all words contained in the vocabulary $V = \{w_1, w_2, w_3, ..., w_N\}$, see Equation (1). Then, we calculate the average word count $\bar{c}_k$ over all words of topic C_k of size $n(C_k)$ $\forall k \in \{1, 2, ..., K\}$, see Equation (2). The adjustment parameter g_{freq} is then calculated according to Equation (3).

$$\bar{c} = \frac{\sum_{i=1}^{N} c_i}{N} \tag{1}$$

$$\bar{c}_k = \frac{\sum_{c_i \in C_k} c_i}{n(C_k)} \tag{2}$$

$$g_{freq,k} = \frac{\bar{c}}{\bar{c}_k} \tag{3}$$

Next, we calculate the word count l_j of each news article $\mathcal{D}_j$ contained in the news corpus $\mathcal{D}$ as well as the average article length $\bar{l}$ over all news articles. The adjustment parameter g_{len} is calculated according to Equation (4). We use the logarithm to avoid over penalizing long news articles. Finally, the topic loading $L_{k,j}$ of topic k on news article j is scaled by Equation (5).

$$g_{len,j} = \frac{log(\bar{l})}{log(l_j)} \tag{4}$$

$$\tilde{L}_{k,j} = L_{k,j} \times g_{freq,k} \times g_{len,j} \tag{5}$$

3.4.2 Visualization of the News Indices

With the scaled topic loadings, calculated over the 4.95 million news articles, we can now visualize the intensities of the individual topics over time. We therefore aggregate the topic loadings at the monthly frequency by summing them up across all news articles published in a given month. In Figure 2 we plot the news index of the physical climate risk topic and in Figure 3 we plot the news indices of the topics “regulatory climate risk” and “sustainability”.

The physical climate risk news index (Figure 2) shows a clear seasonal pattern as it peaks mostly during the months August and September at hurricane season in the U.S. The extreme media coverage of severe hurricanes creates these large peaks that dominate the plot. Other natural disasters such as wildfires, snowstorms, or droughts do not receive as much media attention as hurricanes, making these events difficult to locate in this plot.

In Figure 3 we plot the news indices of regulatory climate risk and sustainability. Regulatory climate risk usually peaks during month where a climate conference takes place. The largest peaks are caused by the Kyoto climate conference (COP 3) in 1997, COP 6-2 in Bonn, COP 13 in Bali, COP 15 in Copenhagen and COP 21 in Paris. Also, we observe that the initial relative low coverage of regulatory climate risk increases from 2005 to 2007. From then on, it fluctuates more or less around this elevated level. At the start of the pandemic in early 2020, both news indices show a sharp decline, as the media attention was centered towards the pandemic. However, later in 2020 we observe a sharp recovery in both indices that slightly exceeds the prior levels.

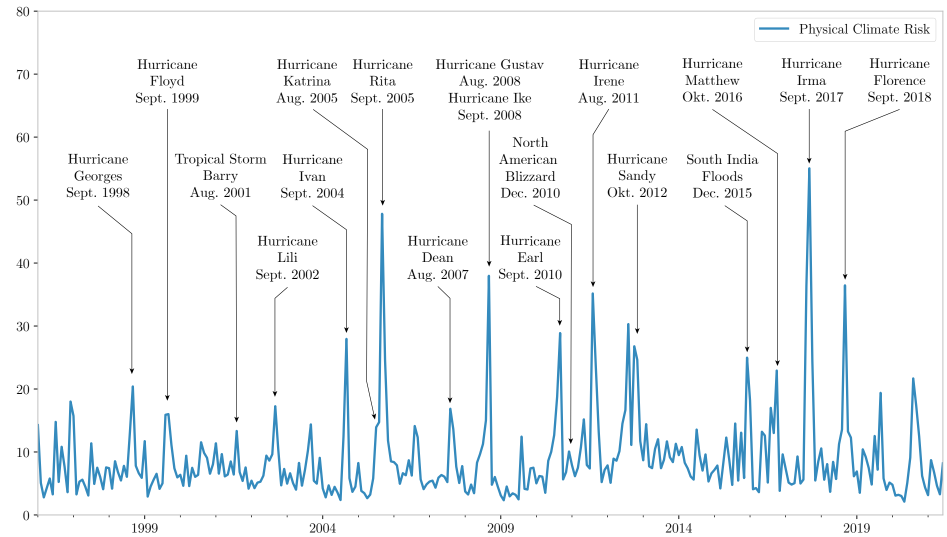


Figure 2: News index showing the monthly aggregate exposure of the topic Physical Climate Risk in Thomson Reuters news over the period Jan. 1996 to July 2021.

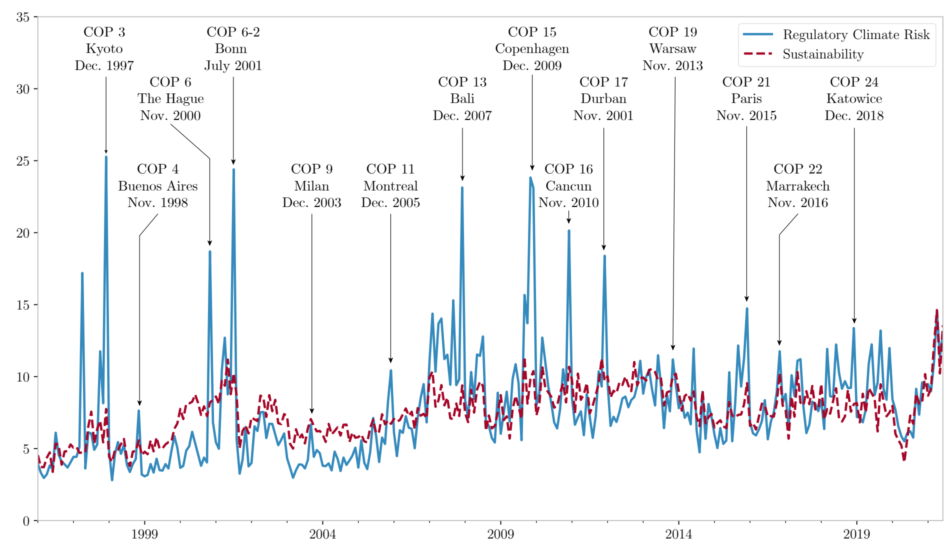


Figure 3: News index showing the monthly aggregate exposure of the topics Regulatory Climate Risk (Transition Risk) and Sustainability in Thomson Reuters news over the period Jan. 1996 to July 2021.

3.4.3 Company-specific News Indices

To obtain company specific news indices $I_{t,k,p}$, we aggregate topic loadings $\tilde{L}_{k,j}$ to daily scores by summing the loadings of all news documents $\mathcal{D}_{t,p}$ published on day t and matched to firm p, see Equation (6). From the 4.95 million news articles associated with the U.S. geography code, we find 2.14 million news articles tagged with at least one ticker code.

$$I_{t,k,p} = \sum_{j \in \mathcal{D}_{t,p}} \tilde{L}_{k,j} \tag{6}$$

Companies have, of course, different levels of coverage, as news about companies with high market capitalization and high media attention is published more frequently than news about companies with low market capitalization and low attention. As a consequence, these large, high-attention firms receive much higher loadings on the topic indices. By selecting the firms with the highest topic loading we would not necessarily select the firms with the highest climate risk or the most sustainable firms, but also the firms with the highest media attention. Therefore, we adjust the daily topic index at the individual firm level by the number of news articles published for each company on a given day $n(\mathcal{D}_{t,p})$ according to Equation (7).

$$\bar{I}_{t,k,p} = \frac{I_{t,k,p}}{n(\mathcal{D}_{t,p})} \tag{7}$$

Sustainability and transition risk encompass concepts that are often discussed in the news together. Transition risks arise as companies transition towards lower environmental footprints. Thus, discussions about this transition can give both green and brown companies a loading on these opposing topics. Experiments show that this can lead to an inaccurate classification of green and brown companies.

To improve the accuracy of our methodology, we first classify news articles into the categories *regulatory climate risk news* and *sustainability news*. As we know the loadings of each news article on all topics, we use this information for the classification. We define a threshold parameter γ that we set to 1.5 and classify a news article as *regulatory climate risk news* if the loading on the regulatory climate risk topic (k=2) is greater than the loading on the sustainability topic (k=1) multiplied by γ.[7]

Analogously we classify a news article as *sustainability news* if the loading on the sustainability topic (k=1) is greater than the loading on the regulatory climate risk topic (k=2) multiplied by γ, see Equation (8). With this classification we obtain 254.317 *regulatory climate risk news* and 414.391 *sustainability news*. Also, we find 89.750 firm-specific news that load on physical climate risk. News articles about physical climate risks are usually explicit, which is why there is no need to classify them into physical climate risk news in advance. Note that all these news articles are matched with one or more firm, since news often affects multiple firms simultaneously.

$$Category = \left\{ \begin{array}{ll} \textit{regulatory climate risk news}, & \text{for } \tilde{L}_{k=2,j} > \gamma \times \tilde{L}_{k=1,j} \\ \textit{sustainability news}, & \text{for } \tilde{L}_{k=1,j} > \gamma \times \tilde{L}_{k=2,j} \end{array} \right\} \tag{8}$$

4 Results

In this Section, we report our main empirical results. Given the multi-step approach that we require to extract signals from news and relate them to equity returns, we proceed as follows. In Section 4.1, we first document the firms and industries most exposed to regulatory climate risk, physical climate risk and sustainability. We do this according to our news-based methodology in order to establish the validity of our identification strategy. In Sections 4.2 and 4.3, we use firm-specific, news-based topic exposures to assess whether climate-related risks are priced in equity markets. In Section 4.4, we extend the sample of firms beyond those explicitly covered in the news by calculating climate-risk related betas and rerun our empirical asset pricing tests. Finally, in Section 4.5 we provide additional evidence validating our main results.

[7] In Dangl and Salbrechter (2023) we show that increasing values of γ are associated with higher classification accuracies. We choose the value of 1.5 to balance the trade-off between improved accuracy and reduced sample size.

4.1 Firm-specific Topic Exposure

We calculate firm-specific topic exposures by summing up the loadings $\bar{I}_{t,k,p}$ over the period Jan. 1996 to Dec. 2020 for the topics (a) regulatory climate risk, (b) physical climate risk and (c) sustainability. As explained before, we consider stocks of the CRSP universe with share codes 10 or 11 that have a market cap above the median market cap in this news-based analysis. The reason being that we need to ensure sufficient media coverage. We also exclude Depository, Credit and Brokerage institutions (SIC sector codes: 60, 61, 62, 66, 67) because they often appear in the news metadata as they provide analyst ratings and reports without being the actual subject of the news. Thus, by including these firms we would significantly overestimate their true risk exposures.

Table 2 highlights the 30 firms with the highest exposures. We observe that the firms listed in (a) are predominantly energy producers or firms related to the Oil and Gas industry. Companies in (b) that are exposed to physical climate risk include also energy producers as well as insurance and food companies. This result seems intuitive, as insurance and food companies are heavily affected by natural disasters and extreme weather events. Companies shown in (c) include solar and renewable energy companies, all of which focus on sustainability in their business models.

Next, we sort firms into major industry groups based on the first two digits of the SIC codes and calculate industry exposures by adding up the exposures of all firms within an industry. Since the number of companies N_i varies considerably across industries, large industries consisting of many companies would be biased to have larger exposures. We therefore adjust the industry exposures by dividing the sum of individual firm-level exposures by $log(N_i)+1$, using the logarithm to avoid overly penalizing large industries.

Table 3 highlights the industries ranked by their adjusted news exposure. We find that *Electric, Gas, And Sanitary Services*, *Coal Mining* and *Petroleum Refining And Related Industries* have the highest exposure to regulatory climate risk, as one would expect. For physical climate risk, we find that the *Insurance Carriers* industry has the second highest exposure and the *Food And Kindred Products* industry has the fourth highest exposure. The high exposures of these industries seem plausible given that both

	(a) Reg. Climate Risk	(b) Phys. Climate Risk	(c) Sustainability
0	Arch Coal Inc	Allstate Corp	First Solar Inc
1	American Electric Power Co Inc	Travelers Companies Inc	Sunpower Corp
2	CNX Resources Corp	PG & E Corp	Canadian Solar Inc
3	Peabody Energy Corp	Consolidated Edison Inc	Clean Energy Fuels Corp
4	Southern Co	Entergy Corp New	Yingli Green Energy Hldg Co Ltd
5	Massey Energy Co	Centerpoint Energy Inc	Trina Solar Limited
6	James River Coal Co	American Electric Power Co Inc	Suntech Power Holdings Co Ltd
7	Cinergy Corp	Dominion Energy Inc	JA Solar Holdings Co Ltd
8	Firstenergy Corp	Chubb Ltd	Jinkosolar Holding Co Ltd
9	Alpha Natural Resources Inc	Chubb Corp	Plug Power Inc
10	Duke Energy Corp New	Hartford Financial Svcs Grp Inc	Green Plains Inc
11	TECO Energy Inc	Duke Energy Corp New	Nextera Energy Inc
12	Cummins Inc	Nextera Energy Inc	Fuelcell Energy Inc
13	Walter Energy Inc	Progress Energy Inc	Energy Conversion Devices Inc
14	NRG Energy Inc	Anadarko Petroleum Corp	Edison International
15	XCEL Energy Inc	Exelon Corp	Hanwha Q Cells Co Ltd
16	Cloud Peak Energy Inc	Eversource Energy	Renesola Ltd
17	Union Pacific Corp	Edison International	Sempra Energy
18	CSX Corp	Archer Daniels Midland Co	PG & E Corp
19	Exelon Corp	Southern Co	LDK Solar Co Ltd
20	CVR Energy	Firstenergy Corp	Sunedison Inc
21	Norfolk Southern Corp	Bunge Ltd	Tesla Inc
22	Valero Energy Corp New	Progressive Corp Oh	AES Corp
23	Public Service Enterprise Gp Inc	OGE Energy Corp	Evergreen Solar Inc
24	Dominion Energy Inc	Everest Re Group Ltd	Enphase Energy Inc
25	Navistar International Corp	Valero Energy Corp New	China Sunergy Co Ltd
26	International Coal Group Inc	APA Corp	Duke Energy Corp New
27	DTE Energy Co	Cincinnati Financial Corp	NRG Energy Inc
28	Nv Energy Inc	Murphy Oil Corp	General Electric Co
29	Pinnacle West Capital Corp	Union Pacific Corp	Ormat Technologies Inc

Table 2: Top 30 companies ranked by their topic exposure to (a) regulatory climate risk, (b) physical climate risk and (c) sustainability. The topic exposure is calculated over the period Jan 1996 to Dec. 2020.

are highly exposed to the risk of damages caused by natural disasters.

Furthermore, the industries most exposed to the Sustainability topic are *Electronic And Other Electrical Equipment*, *Electric Gas And Sanitary Services*, *Chemicals And Allied Products* and *Business Services*. Interestingly, we observe an overlap of some Industries (e.g. *Electric Gas And Sanitary Services*, *Oil And Gas Extraction*, *Chemicals And Allied Products*, *Transportation Equipment*) having a pronounced exposure to all three topics. One explanation of this finding is that firms within these industries exhibit a particularly high variation of firm-specific climate risk exposures.

	(a) Reg. Climate Risk	Exposure	(b) Phys. Climate Risk	Exposure	(c) Sustainability	Exposure
0	Electric, Gas, And Sanitary Services	2069.45	Electric, Gas, And Sanitary Services	1585.48	Electronic And Other Electrical Equipment And ...	3531.45
1	Coal Mining	1088.46	Insurance Carriers	891.04	Electric, Gas, And Sanitary Services	2868.70
2	Petroleum Refining And Related Industries	504.30	Oil And Gas Extraction	580.54	Chemicals And Allied Products	1497.82
3	Oil And Gas Extraction	414.17	Food And Kindred Products	348.00	Business Services	1469.73
4	Chemicals And Allied Products	392.45	Chemicals And Allied Products	308.21	Oil And Gas Extraction	1413.57
5	Transportation Equipment	365.36	Transportation By Air	277.27	Industrial And Commercial Machinery And Comput...	1071.44
6	Railroad Transportation	295.15	Petroleum Refining And Related Industries	265.14	Transportation Equipment	764.44
7	Industrial And Commercial Machinery And Comput...	246.10	Apparel And Accessory Stores	235.66	Measuring, Analyzing, And Controlling Instrume...	654.41
8	Food And Kindred Products	232.01	Electronic And Other Electrical Equipment And ...	204.78	Nonclassifiable Establishments	592.12
9	Primary Metal Industries	227.50	Industrial And Commercial Machinery And Comput...	197.51	Communications	580.67
10	Business Services	203.65	General Merchandise Stores	194.10	Engineering, Accounting, Research, Management,...	527.05
11	Water Transportation	181.21	Business Services	186.84	Food And Kindred Products	381.80
12	Communications	175.60	Insurance Agents, Brokers, And Service	181.89	Apparel And Accessory Stores	348.05
13	Insurance Carriers	174.79	Railroad Transportation	180.08	Insurance Carriers	313.66
14	Electronic And Other Electrical Equipment And ...	131.56	Transportation Equipment	165.65	Petroleum Refining And Related Industries	262.34
15	Transportation By Air	123.38	Automotive Dealers And Gasoline Service Stations	147.53	Miscellaneous Retail	227.66
16	Metal Mining	115.07	Communications	147.47	Primary Metal Industries	225.23
17	Measuring, Analyzing, And Controlling Instrume...	86.17	Eating And Drinking Places	131.91	General Merchandise Stores	200.58
18	Fabricated Metal Products, Except Machinery An...	79.72	Miscellaneous Retail	114.35	Fabricated Metal Products, Except Machinery An...	193.97
19	Automotive Dealers And Gasoline Service Stations	74.63	Pipelines, Except Natural Gas	109.67	Transportation By Air	193.16

Table 3: Top 20 industries with the highest exposure to (a) regulatory climate risk, (b) physical climate risk and (c) sustainability. The topic exposure is calculated over the period Jan. 1996 to Dec. 2020.

To better understand the time-series variation, we plot the firm-specific news exposures over the period Jan. 1999 to Dec. 2020 for the firms Allstate (ALL), Apple (AAPL), Exxon Mobil (XOM), Procter&Gamble (PG), Union Pacific (UNP) and Nextera Energy (NEE) in Figure 4 and 5. We smooth the monthly observations over two-year rolling windows using arithmetic means.

Figure 4 shows the firm-specific exposure to physical climate risk. As expected, we observe a high exposure for the insurance company Allstate (blue line). Exxon Mobil, Union Pacific and Nextera Energy also have significant exposures throughout the sample period. In contrast, the physical climate risk of Apple and Procter&Gamble is close to zero (red and green lines).

In Figure 5 we subtract the exposure to regulatory risk from the exposure to sustainability. Positive values indicate green firms, negative values indicate brown firms. Put differently, we calculate a measure of green-minus-brown exposure. We observe that Nextera Energy is a sustainable firm according to this measure, as it has the largest positive exposure. Also, Apple, Procter&Gamble and Allstate have positive exposures on average, but of smaller magnitudes. Union Pacific and Exxon Mobil both show strong negative exposures. We would, thus, classify them as being strongly exposed to regulatory risk.

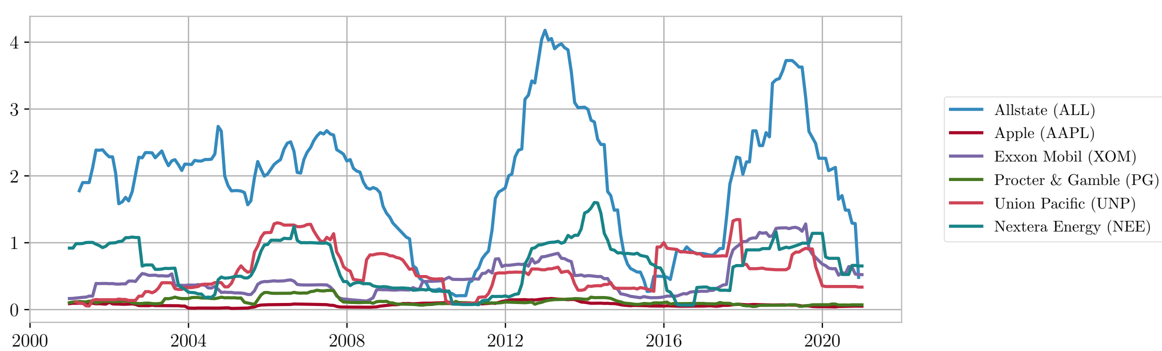


Figure 4: Firm-specific news indices showing the exposure of individual firms to physical climate risk over the period Jan. 1999 to Dec. 2020. We smooth the values by calculating the mean over a two-year rolling window.

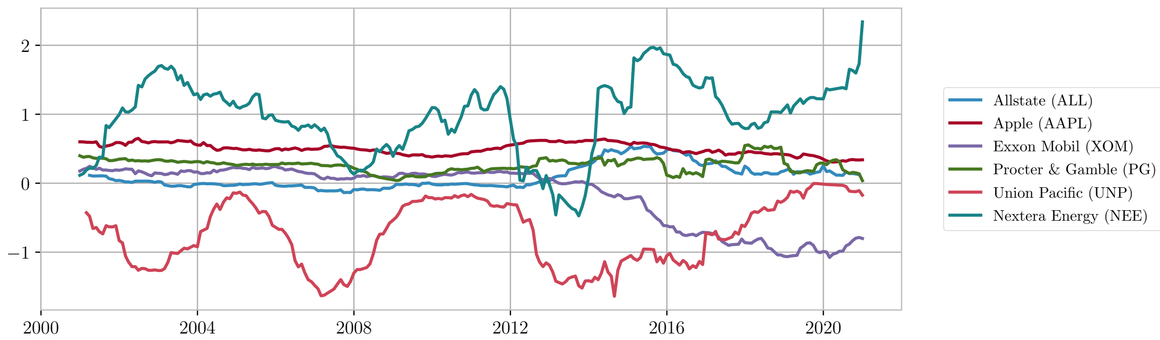


Figure 5: We subtract the firm-specific exposure to transition risk from the exposure to sustainability after calculating means over two-year rolling windows (green-minus-brown). The Figure shows the green-minus-brown news indices for individual firms. Positive (negative) values indicate a high exposure to sustainability (transition risk) relative to the exposure to transition risk (sustainability).

4.2 Topic Exposure Sorted Climate Risk Portfolios

To assess the return implications of our news-based exposures, we form zero-investment portfolios. We identify green and brown firms based on their exposures to the topics sustainability (k=1) and regulatory climate risk (k=2). To determine the constituents of this green-minus-brown (GMB) portfolio, we measure each firm's topic exposure, denoted as $\bar{E}_{t,k,p}$, over a 24-month rolling window in accordance with Equation (9). Since we will use these exposures also to determine portfolio weights and their distribution across firms can be highly skewed, we apply a log-transformation.

In a next step we calculate measures of relative exposure between green and brown stocks by subtracting the exposures to regulatory climate risk from the exposures to sustainability at the individual firm level ($\tilde{E}_{t,p}$). After ranking the firms from high to low we form portfolios by putting stocks in the top decile into the "Green" portfolio and stocks in the bottom decile into the "Brown" portfolio. We then weight firms, within these portfolios, relative to their topic index exposures. The portfolio weights are calculated according to Equation (10) with the topic exposures of top (bottom) decile stocks $\tilde{E}^{top}_{t,p}$ ($\tilde{E}^{bottom}_{t,p}$). We study monthly returns and re-balance at the end of each month.

$$\bar{E}_{t,k,p} = \log\left(\sum_{t-25}^{t-1} \bar{I}_{t,k,p}\right) \tag{9}$$

$$w_{t,p,green} = \frac{\tilde{E}^{top}_{t,p}}{\sum\limits_{p} \tilde{E}^{top}_{t,p}} \qquad \text{and} \qquad w_{t,p,brown} = \frac{\tilde{E}^{bottom}_{t,p}}{\sum\limits_{p} \tilde{E}^{bottom}_{t,p}} \tag{10}$$

Similar to the GMB portfolio, we also calculate a topic-exposure weighted long-only physical climate risk portfolio that includes the top decile of firms ranked by their news-based exposures to physical climate risk ($\bar{E}_{t,k=3,p}$) with weights calculated according to Equation (11). In addition, we construct a long-short, high-minus-low physical climate risk portfolio, denoted as PhysCR, where we go long in the topic-exposure weighted portfolio of stocks with high physical climate risk and short in all remaining stocks, i.e., all stocks with no exposure to physical climate risk over the previous 24-month rolling window period. Since these stocks are equal in regard to their topic exposure, we weight them equally.

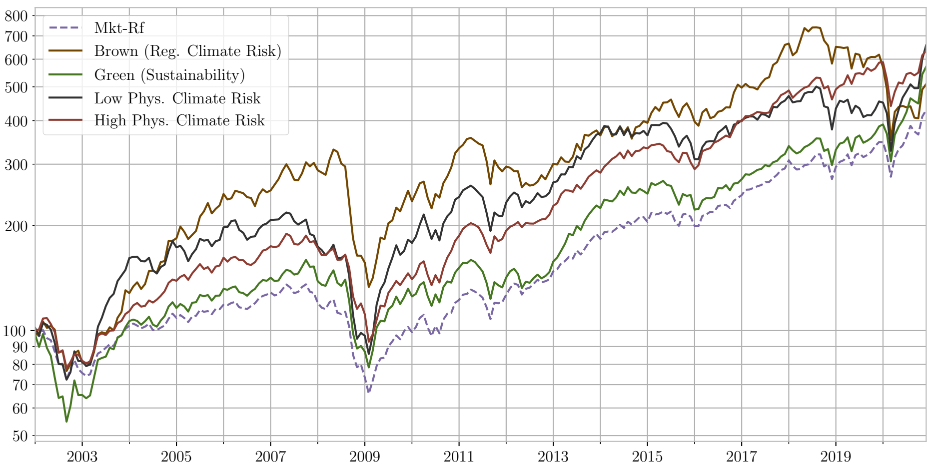
$$w_{t,p,phys} = \frac{\bar{E}^{top}_{t,k=3,p}}{\sum\limits_{p} \bar{E}^{top}_{t,k=3,p}} \tag{11}$$

Figure 6a shows the cumulative excess returns (in excess of the risk-free rate) of the "Green" and "Brown" portfolios, and of the portfolios with high and low physical climate risk over the period Jan. 2002 to Dec. 2020. Figure 6b displays the performance of the GMB and PhysCR portfolio over the same period.

We observe that green stocks underperform brown stocks until 2011 (blue line). In 2011, the trend changes and from 2012 to 2014, we observe a strong outperformance of green over brown stocks. This upward trend, however, is interrupted during the four-year period 2015 to 2018. In 2015, green companies record a negative annual return, while the brown stock portfolio closes more or less at the same level as at the beginning of the year. In the years that follow, brown firms experience windfall gains due to the Trump administration's policies leading to a further decline of the news-exposure-weighted GMB portfolio. From 2018, green stocks continue their upward trend until the end of the observation period.

For the high-minus-low physical climate risk portfolio (PhysCR) in Figure 6b (brown line) we observe a steady upward trend from 2010 to 2019, indicating a stronger performance of the portfolio of stocks with exposure to physical climate risks compared to the equal weighted portfolio of stocks with low physical climate risk exposure. However, two pronounced drawdowns – one in 2009, after the great financial crisis, and one in 2020, after the coronavirus crash – also stand out. In both cases, the drawdown is caused by a quicker recovery of the low physical climate risk portfolio relative to the high physical climate risk portfolio (see Figure 6a). One explanation could be that, at least during the 2020 pandemic, the demand and prices of internet firms, which tend to be firms with low physical climate risk, surged. This contributed to the weak relative performance of firms with high physical climate risk.

(a)



(b)

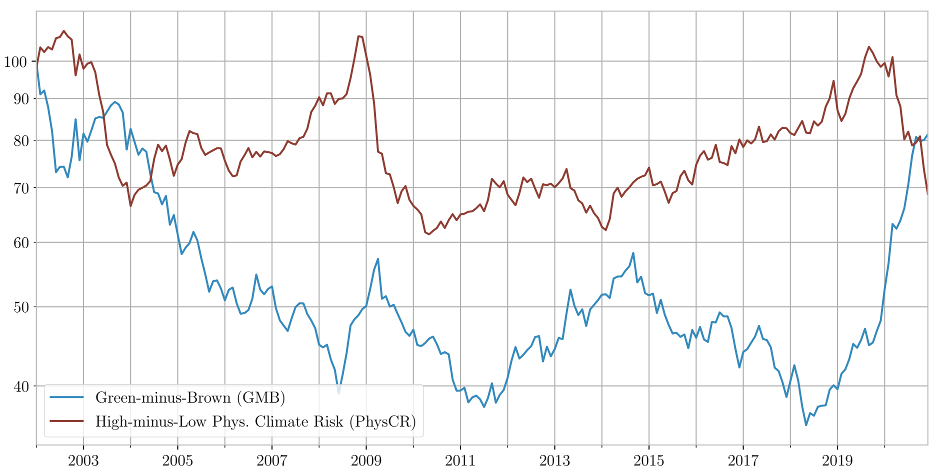


Figure 6: Cumulative returns of the topic-exposure weighted (a) “Green” (sustainability), “Brown” (regulatory climate risk), high- and low physical climate risk portfolio and (b) the green-minus-brown (GMB) and high-minus-low physical climate risk (PhysCR) portfolio over the period from Jan. 2002 to Dec. 2020.

Table 4 reports the summary statistics of the portfolio returns for the periods Jan. 2002 to Dec. 2020 (Panel A), Jan. 2002 to Dec. 2011 (Panel B), and Jan. 2012 to Dec. 2020 (Panel C). Over the full period (Panel A) the “High Physical Climate Risk Portfolio” has a similar cumulative performance as the “Green Portfolio” with values of 534.52% and 471.29% respectively. Thus, both portfolios outperform the value-weighted market portfolio with a cumulative performance of 329.25%.

On a risk-adjusted basis we observe the highest Sharpe-Ratio for the “High Physical

Climate Risk Portfolio" followed by the market portfolio and the "Green Portfolio" with values of 0.64, 0.52 and 0.48, respectively. Overall, the equal-weighted "Low Physical Climate Risk Portfolio" has the highest cumulative performance over the full period (558.59%), which is consistent with existing evidence that the 1/N portfolio is a hard benchmark to beat (DeMiguel et al., 2009).

Over the full period the GMB portfolio has a cumulative return of -18.67%. In Panel B, the GMB portfolio has cumulative returns of -60.45% and a compounded annual growth rate (CAGR) of -8.93% while during the second subperiod, starting in 2012 (Panel C), the GMB portfolio has a performance of 105.65% with an CAGR of 8.34% and a Sharpe-Ratio of 0.64. Also, the "High Physical Climate Risk Portfolio" outperforms the "Low Physical Climate Risk Portfolio" over the period 2012 to 2020 in absolute and risk-adjusted performance with Sharpe-Ratios of 1.08 vs. 0.67.

The average portfolio sizes indicate a substantially higher number of constituents in the "Green" portfolio relative to the "Brown" and the "High Physical Climate Risk" portfolios (see Table 4). This is the case since we only consider stocks with a meaningful exposures to these topics in the rolling window aggregation of news and, therefore, exclude firms with topic exposures below a pre-defined threshold.

Portfolio	Performance (%)	CAGR (%)	SD (%)	Sharpe Ratio	Drawdown (%)	Drawdown (months)	Avg. Portf. Size	CAPM Beta	CAPM Beta (t-value)
Panel A: Full Period, Jan. 2002 to Dec. 2020									
Green (Sustainability)	471.29	9.61	19.82	0.48	-50.83	65.0	174.32	1.23	45.89
Brown (Reg. Climate Risk)	409.14	8.94	23.09	0.39	-59.65	33.0	65.52	1.25	21.97
GMB	-18.67	-1.08	13.71	-0.08	-64.07	228.0		-0.01	-0.24
High Physical Climate Risk	534.52	10.21	15.85	0.64	-50.99	46.0	54.39	0.94	32.10
Low Physical Climate Risk	558.59	10.43	21.87	0.48	-60.71	43.0	3256.02	1.30	33.15
Mkt-Rf	329.25	7.97	15.28	0.52	-51.44	54.0		1.00	inf
Panel B: Period Jan. 2002 to Dec. 2011									
Green (Sustainability)	32.99	2.92	21.63	0.13	-50.83	51.0	188.82	1.26	32.16
Brown (Reg. Climate Risk)	186.07	11.18	24.01	0.47	-59.65	33.0	57.13	1.25	17.36
GMB	-60.45	-8.93	13.86	-0.64	-62.17	120.0		0.01	0.11
High Physical Climate Risk	83.03	6.29	17.52	0.36	-50.99	46.0	49.88	1.00	26.99
Low Physical Climate Risk	112.77	7.91	23.50	0.34	-60.71	43.0	3587.71	1.33	25.06
Mkt-Rf	20.63	1.91	16.22	0.12	-51.44	51.0		1.00	inf
Panel C: Period Jan. 2012 to Dec. 2020									
Green (Sustainability)	329.57	17.58	17.51	1.00	-21.70	6.0	158.20	1.19	33.28
Brown (Reg. Climate Risk)	77.98	6.61	22.12	0.30	-52.47	29.0	74.84	1.29	14.55
GMB	105.65	8.34	13.12	0.64	-38.49	67.0		-0.10	-1.05
High Physical Climate Risk	246.67	14.81	13.76	1.08	-25.15	11.0	59.42	0.86	18.41
Low Physical Climate Risk	209.54	13.38	19.99	0.67	-34.59	25.0	2887.47	1.30	22.33
Mkt-Rf	255.85	15.15	14.01	1.08	-20.48	8.0		1.00	inf

Table 4: Portfolio statistics calculated over the periods Jan. 2002 to Dec. 2020 (Panel A), Jan. 2002 to Dec. 2011 (Panel B) and Jan. 2012 to Dec. 2020 (Panel C)

Table 5 shows the average weights of the top 30 holdings of the "Green" and "Brown" portfolio calculated over the period Jan. 2002 to Dec. 2020. Note that due to averaging over time some firms appear in both portfolios. Firms, however, can only be in one portfolio at a specific point in time.

For the regulatory climate risk ("Brown") portfolio the largest holdings are Oil and Gas firms like Exxon Mobil and Chevron, energy suppliers such as American Electric Power and Duke Energy Corp. as well as railway companies such as Union Pacific. Companies involved in the energy business, such as Consolidated Edison or PG&E, are also highly exposed to physical climate risk, along with insurance companies such as Allstate and Travelers Companies. The largest holdings of the sustainability ("Green") portfolio are technology firms like Apple, Microsoft and Alphabet as well as energy companies such as First Solar and Sunpower and telecommunication firms like AT&T and Verizon Communications.

	Regulatory Climate Risk (Brown) Portfolio			Physical Climate Risk Portfolio			Sustainability (Green) Portfolio		
	Weight (%)		Company Name	Weight (%)		Company Name	Weight (%)		Company Name
0	3.07	3.07	American Electric Power Co Inc	2.36	2.36	Allstate Corp	1.42	1.42	General Electric Co
1	2.71	5.78	CNX Resources Corp	1.85	4.21	Entergy Corp New	1.38	2.80	Apple Inc
2	2.44	8.22	Southern Co	1.73	5.94	Consolidated Edison Inc	1.36	4.16	Microsoft Corp
3	2.35	10.57	Arch Coal Inc	1.71	7.65	Travelers Companies Inc	1.28	5.44	Intel Corp
4	2.31	12.88	Peabody Energy Corp	1.62	9.27	Hartford Financial Svcs Grp Inc	1.19	6.64	Alphabet Inc
5	2.27	15.15	Valero Energy Corp New	1.53	10.80	Anadarko Petroleum Corp	1.18	7.82	International Business Machs Cor
6	1.91	17.06	Massey Energy Co	1.53	12.33	Centerpoint Energy Inc	1.11	8.93	Boeing Co
7	1.60	18.66	CSX Corp	1.41	13.74	APA Corp	1.08	10.01	Lockheed Martin Corp
8	1.53	20.19	Exxon Mobil Corp	1.35	15.10	Dominion Energy Inc	1.07	11.08	Cisco Systems Inc
9	1.45	21.65	Union Pacific Corp	1.29	16.38	PG & E Corp	1.02	12.10	First Solar Inc
10	1.45	23.09	Firstenergy Corp	1.22	17.61	Valero Energy Corp New	0.98	13.07	Walmart Inc
11	1.36	24.45	Cummins Inc	1.19	18.79	American Electric Power Co Inc	0.98	14.05	Qualcomm Inc
12	1.32	25.77	United States Steel Corp New	1.17	19.97	Duke Energy Corp New	0.97	15.02	Amazon Com Inc
13	1.27	27.04	Duke Energy Corp New	1.14	21.10	Nextera Energy Inc	0.95	15.96	HP Inc
14	1.26	28.30	Norfolk Southern Corp	1.12	22.23	Union Pacific Corp	0.91	16.87	Sunpower Corp
15	1.14	29.44	Chevron Corp New	1.02	23.25	Cincinnati Financial Corp	0.91	17.78	Pfizer Inc
16	1.14	30.58	Cinergy Corp	1.02	24.27	Jetblue Airways Corp	0.89	18.67	Oracle Corp
17	1.13	31.71	XCEL Energy Inc	1.02	25.29	OGE Energy Corp	0.86	19.53	Merck & Co Inc New
18	1.12	32.83	Phillips 66	1.01	26.30	Southern Co	0.84	20.38	AT & T Inc
19	1.10	33.93	NRG Energy Inc	1.01	27.30	Exxon Mobil Corp	0.83	21.21	Verizon Communications Inc
20	1.07	35.00	Marathon Petroleum Corp	0.98	28.29	CSX Corp	0.83	22.04	Tesla Inc
21	1.04	36.04	Exelon Corp	0.97	29.25	Chubb Corp	0.81	22.84	Raytheon Technologies Corp
22	1.03	37.07	Archer Daniels Midland Co	0.96	30.21	Murphy Oil Corp	0.79	23.63	Johnson & Johnson
23	1.01	38.09	AK Steel Holding Corp	0.95	31.16	Exelon Corp	0.77	24.40	Advanced Micro Devices Inc
24	1.00	39.09	Newmont Corp	0.95	32.11	Archer Daniels Midland Co	0.76	25.16	PG & E Corp
25	0.93	40.02	Du Pont EI De Nemours & Co	0.94	33.05	Conocophillips	0.75	25.91	Nextera Energy Inc
26	0.92	40.94	Hollyfrontier Corp	0.91	33.96	Tyson Foods Inc	0.73	26.65	Northrop Grumman Corp
27	0.86	41.79	Nucor Corp	0.91	34.87	Marathon Oil Corp	0.70	27.35	Procter & Gamble Co
28	0.85	42.65	Burlington Northern Santa Fe Cp	0.90	35.77	Progress Energy Inc	0.70	28.05	Sempra Energy
29	0.84	43.49	Vectren Corp	0.90	36.66	Aon Plc New	0.70	28.74	Yahoo Inc

Table 5: Top 30 companies of the regulatory climate risk (Brown), physical climate risk and sustainability (Green) portfolios. The weights are averages in %, calculated over the period Jan. 2002 to Dec. 2020.

Next, we calculate correlations between the climate-related risk factors, i.e., the green-minus-brown (GMB) portfolio and the high-minus-low physical climate risk portfolio (PhysCR), and the standard Fama-French risk factors, i.e., the market factor (Mkt-Rf), size factor (SMB), value factor (HML), profitability factor (RMW), the investment factor (CMA) and the momentum factor (UMD), using monthly returns over the period Jan. 2002 to Dec. 2020 (Table 6, Panel A) and Jan. 2012 to Dec. 2020 (Table 6, Panel B). In addition, we include individual climate risk related portfolios also as long-only portfolios in the analysis.

For Panel A, we observe a negative correlation between GMB and HML of -0.30, suggesting that green stocks are rather growth stocks and brown stocks are rather value stocks. Also, green stocks exhibit weaker operating profitability than brown stocks since the correlation of GMB with RMW is -0.255. This changes for the period starting in 2012 (Panel B) where the correlation with RMW becomes slightly positive. Moreover, the correlations with CMA, SMB and HML become increasingly negative. Thus, green firms tend to be large, aggressively investing growth stocks while brown firms tend to be small, conservatively investing value stocks. Pástor et al. (2022) show that the brown nature of value stocks has a significant contribution to the poor performance of the value strategy in recent years, just as the green nature of momentum stocks explains the positive performance of the momentum strategy experienced during the most recent period.

The high physical climate risk portfolio (High Phys. CR) has positive correlation coefficients with SMB and HML, with values of 0.482 and 0.366, respectively, indicating that firms exposed to physical climate risks are rather small value stocks. The correlations with CMA, RMW and GMB are 0.10, -0.297 and -0.194. For the period staring in 2012 the correlation of the high physical climate risk portfolio with GMB becomes -0.303 which indicates that brown firms tend to be more affected by physical climate risks than green firms. Furthermore, the GMB portfolio and the high-minus-low physical climate risk portfolio (PhysCR) are slightly negatively correlated with a coefficient of -0.16.

	PhysCR	Green	Brown	High Phys. CR	Low Phys. CR	Mkt-RF	SMB	HML	CMA	RMW	UMD
Panel A: Full Period, July 2002 to July 2021											
GMB	-0.160	0.088	-0.518	-0.194	-0.057	-0.016	-0.256	-0.300	-0.061	-0.255	-0.144
PhysCR		-0.579	-0.402	-0.268	-0.716	-0.488	-0.575	-0.013	0.025	0.519	0.407
Green			0.806	0.855	0.922	0.950	0.421	0.163	-0.005	-0.485	-0.535
Brown				0.850	0.825	0.825	0.513	0.318	0.032	-0.265	-0.374
High Phys. CR					0.865	0.906	0.482	0.366	0.100	-0.297	-0.446
Low Phys. CR						0.911	0.649	0.272	0.059	-0.485	-0.535
Mkt-RF							0.396	0.232	0.000	-0.389	-0.478
SMB								0.360	0.155	-0.280	-0.198
HML									0.433	0.004	-0.343
CMA										-0.070	-0.119
RMW											0.313
Panel B: Period July 2012 to July 2021											
GMB	-0.025	-0.023	-0.612	-0.303	-0.195	-0.102	-0.454	-0.481	-0.258	0.051	0.134
PhysCR		-0.635	-0.488	-0.264	-0.748	-0.543	-0.630	0.018	0.253	0.390	0.422
Green			0.805	0.823	0.926	0.955	0.468	0.195	-0.143	-0.048	-0.566
Brown				0.831	0.848	0.816	0.640	0.439	0.039	-0.069	-0.528
High Phys. CR					0.838	0.873	0.494	0.400	0.041	0.069	-0.527
Low Phys. CR						0.908	0.697	0.265	-0.115	-0.173	-0.602
Mkt-RF							0.420	0.216	-0.140	0.024	-0.505
SMB								0.360	0.006	-0.326	-0.432
HML									0.508	0.070	-0.506
CMA										0.106	-0.192
RMW											-0.065

Table 6: Correlations among risk factors calculated using monthly returns over the period Jan. 2002 to Dec. 2020 (Panel A) and the period Jan. 2012 to Dec. 2020 (Panel B). "GMB" denotes the green-minus-brown portfolio and "PhysCR" denotes the high-minus-low physical climate risk portfolio.

4.3 Climate Risk Premia

To more systematically assess the return implications of climate-risk related news exposures, we perform Fama-MacBeth cross-sectional regressions (see, Equation (12)) with firm specific characteristics, i.e., the firm-specific exposures to the topics regulatory climate risk (Reg), physical climate risk (Phys) and sustainability (Sus). In addition, we consider firm characteristics standard in the empirical asset pricing literature, namely CAPM beta, size, as measured by the log of market capitalization (*log_mktcap*), book-to-market ratio (*B2M*), operating profitability (*OP*), and investment (*INV*) as explanatory variables.[8]

Equation (12) shows the details of the Fama-MacBeth regression. $R_{p,t} - R_{f,t}$ is the return of stock p in month t in excess of the risk free rate $R_{f,t}$. We load corporate financial data from Compustat and calculate B2M, OP and INV as described by Fama and French (1992, 2015). To avoid a look ahead bias, we calculate all metrics as at the end of July using data from the previous fiscal year.

[8] The CAPM beta is estimated over a rolling window of 60 months of monthly return data. In case of missing values we calculate betas if at least 36 months of return data are available.

$$R_{p,t} - R_{f,t} = \delta_{0,t} + \delta_{1,t}\beta_{p,t-1} + \delta_{2,t}Size_{p,t-1} + \delta_{3,t}B2M_{p,t-1} + \delta_{4,t}OP_{p,t-1} + \delta_{5,t}INV_{p,t-1} + \delta_{6,t}Sus_{p,t} + \delta_{7,t}Reg_{p,t} + \delta_{8,t}Phys_{p,t} + \epsilon_{p,t} \quad (12)$$

We report the results of the Fama-MacBeth regressions in Table 7 showing the annualized risk premia with the corresponding t-statistics. In total, we estimate seven models, starting with Model 1 that focuses on the classic Fama and French five-factor model. We estimate Model 1 on the full CRSP universe, only excluding penny stocks, with 810.766 observations (Model 1a). The purpose of this model is to establish a first and very general basecase result using the standard controls.

We then rerun the basecase specification on the smaller sample of firms, for which we have news-based climate risk exposures (Model 1b), giving us 189.586 monthly observations. Model 1b acts as the main baseline for comparison with Model 5 that contains all climate characteristics, as well as models 6 and 7 where we further control for fixed effects using 10 sector dummies (Model 6) or 65 industry dummies (Model 7). Models 2 to 4 are univariate extensions of Model 1a where we add each climate risk related exposure individually. We omit those results for the sake of brevity (see the full Table 17 in the Appendix).

Adding the news-based climate risk related factors to the baseline model, i.e., when comparing Model 5 to Model 1b, we observe an increase in adjusted R^2 from 5.43% to 6.26% (6.01% to 7.10% for the first- and 4.78% to 5.32% for the second subperiod). In relative terms, this means an increase of 15.3% for the full period, 18.1% in the first- and 11.3% in the second subperiod.

Considering Model 5, we find a significant positive risk premium of 1.50% p.a. (t-value = 2.37) for physical climate risk over the full period (Jan. 2002 to Dec. 2020). Thus, a one standard deviation increase in the exposure to physical climate risk leads to a positive risk premium of 1.50% p.a. This result is robust when controlling for fixed effects (Model 6 and 7), as the risk premium even increases to 1.75% p.a. (t-value = 2.73) with sector fixed effects and 1.94% p.a. (t-value = 3.38) with industry fixed effects. This indicates further that the risk premium for physical climate risk is a firm-specific effect rather than a sector- or industry-specific effect.

The risk premium for regulatory climate risk is positive in the first subperiod (Model 5, Jan. 2002 to Dec. 2011) with a coefficient of 1.54% p.a. (t-value 1.61) and significantly negative in the second subperiod (Jan. 2012 to Dec. 2020) with a value of -2.56% p.a. (t-value = -2.94). As a consequence, the change in the premium over the two subperiods leads to an insignificant premium over the full period. These findings are in line with the literature. Hsu et al. (2022) finds a positive premium for firms with high toxic emissions over low emitting firms for the period 1996 to 2016 of 4.42% p.a. In contrast, Pástor et al. (2022) finds a strong outperformance of green stocks over brown stocks for the period 2013 to 2020. These contradictory results, most likely, emerge in response to the pronounced shift towards increased ESG awareness and "green investing", which caused a noticeable increase in demand for green stocks relative to brown stocks.

Interestingly, the risk premium for regulatory climate risk becomes more significant in the first subperiod (t-values = 1.61/2.38/2.34 for Model 5/6/7) and less significant in the second subperiod (t-values = -2.56/-1.66/-0.69 for Model 5/6/7) when we also control for sector and industry dummies. This indicates that in the first subperiod the regulatory climate risk premium is determined by firm-specific effects, while in the second subperiod whole industries and sectors are affected. Especially the sector *Mining* shows a sharp decline in sector average returns form the first to the second subperiod.

The coefficients of exposures to sustainability always have the opposite sign compared to those of regulatory climate risk which gives further support for a shift towards "green investing". Also, we observe that the coefficients become less significant after controlling for sector and industry fixed effects in the first- (t-values = -1.24/-1.17/-0.29 for Models 5/6/7) and second subperiod (t-values = 1.39/0.95/0.67 for Models 5/6/7). Thus, again whole industries benefit, while others suffer from the transition towards more sustainable societies.

Among the other explanatory variables, only *size* turns out to be significant over the entire period in case of the full model (Model 5) and after controlling for firm- and sector fixed effects (models 6 and 7). In the second subperiod, the coefficient of the market-beta becomes significantly negative once we control for fixed effects. Overall, traditional firm characteristics do not seem to play an important role, not in absolute terms and not relative to climate-related exposures, in these regressions.

	Model 1a			Model 1b			Model 5			Model 6			Model 7		
Period	Full	1	2	Full	1	2	Full	1	2	Full	1	2	Full	1	2
Const	12.64	10.48	15.03	11.46	8.96	14.24	11.46	8.96	14.24						
	(2.46)	(1.26)	(2.63)	(2.19)	(1.06)	(2.44)	(2.19)	(1.06)	(2.44)						
Beta	-2.91	-0.61	-5.48	-0.86	0.81	-2.73	-0.64	1.18	-2.67	-0.85	1.05	-2.95	-1.40	0.55	-3.55
	(-2.16)	(-0.29)	(-3.66)	(-0.64)	(0.36)	(-2.02)	(-0.49)	(0.57)	(-1.95)	(-0.64)	(0.49)	(-2.16)	(-1.25)	(0.32)	(-2.86)
Size	7.01	5.09	9.15	5.83	3.98	7.88	6.21	4.32	8.30	6.83	4.60	9.31	7.08	4.75	9.68
	(5.24)	(2.50)	(5.76)	(3.24)	(1.47)	(3.54)	(3.21)	(1.45)	(3.63)	(3.65)	(1.60)	(4.22)	(4.14)	(1.84)	(4.73)
B2M	-2.17	-2.28	-2.05	-2.30	-0.89	-3.87	-2.28	-1.23	-3.44	-1.51	-0.88	-2.20	-1.30	-0.75	-1.92
	(-1.76)	(-1.18)	(-1.36)	(-1.45)	(-0.37)	(-1.93)	(-1.48)	(-0.54)	(-1.69)	(-1.02)	(-0.39)	(-1.19)	(-0.87)	(-0.32)	(-1.07)
OP	0.54	0.50	0.57	-0.60	-0.89	-0.27	-0.56	-0.90	-0.17	-0.53	-1.01	0.01	-0.73	-1.12	-0.29
	(0.92)	(0.76)	(0.58)	(-0.83)	(-0.94)	(-0.25)	(-0.78)	(-0.94)	(-0.16)	(-0.79)	(-1.08)	(0.01)	(-1.14)	(-1.22)	(-0.33)
INV	0.32	-0.82	1.58	0.37	-0.37	1.19	0.42	-0.23	1.14	0.22	-0.55	1.07	0.49	-0.08	1.11
	(0.54)	(-0.95)	(2.19)	(0.54)	(-0.40)	(1.19)	(0.63)	(-0.25)	(1.15)	(0.34)	(-0.66)	(1.14)	(0.81)	(-0.09)	(1.27)
Sus							-0.05	-1.38	1.44	-0.10	-1.06	0.96	0.20	-0.24	0.69
							(-0.06)	(-1.24)	(1.39)	(-0.15)	(-1.17)	(0.95)	(0.31)	(-0.29)	(0.67)
Reg							-0.40	1.54	-2.56	0.28	2.04	-1.66	0.60	1.75	-0.69
							(-0.57)	(1.61)	(-2.94)	(0.45)	(2.38)	(-2.08)	(1.04)	(2.34)	(-0.85)
Phys							1.50	2.08	0.85	1.75	2.17	1.27	1.94	2.15	1.70
							(2.37)	(2.23)	(1.04)	(2.73)	(2.34)	(1.47)	(3.38)	(2.67)	(2.08)
Fixed effects	None			None			None			Sector fixed effects			Industry fixed effects		
Months	228	120	108	228	120	108	228	120	108	228	120	108	228	120	108
Observations	810766	810766	810766	189586	189586	189586	189586	189586	189586	189586	189586	189586	189586	189586	189586
Firms	8151	8151	8151	3005	3005	3005	3005	3005	3005	3005	3005	3005	3005	3005	3005
R2 (%)	2.86	3.12	2.57	6.04	6.65	5.37	7.24	8.11	6.26	11.36	12.77	9.79	29.20	32.70	25.32
Adj. R2 (%)	2.71	2.99	2.40	5.43	6.01	4.78	6.26	7.10	5.32	9.41	10.80	7.87	22.63	26.17	18.70

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7: Fama-MacBeth regression performed over the periods Jan. 2002 to Dec. 2020 (Full), and the two subperiods Jan. 2002 to Dec. 2011 (1) and Jan. 2012 to Dec. 2020 (2). Model 1 is comprised of the classic risk factors that enter the Fama-French five-factor model. Models 2 to 4 are univariate extensions of the Fama-French 5-factor model, which we omit for the sake of brevity (see the full Table 17 in the Appendix). In Model 5 we include the climate factors and in Model 6 and 7 we control for fixed effects using sector dummies in Model 6 and industry dummies in Model 7. We consider 10 sectors (divisions) and 65 industries (with at least 1000 observations each) according to the SIC scheme. We report the annualized risk premia in percent and heteroskedasticity and autocorrelation (HAC) adjusted t-values (Newey and West (1986) standard errors with three lags). All characteristics except dummy variables are standardized for each of the n cross-sectional regressions. Also we exclude all observations with missing values in the cross sectional regression which causes the number of observations to decline relative to Model 1 as the number of firms with topic exposures is limited.

4.4 Climate Risk Betas

A limitation to consider when using firm-specific news exposures is the limited coverage, as not all firms are consistently mentioned in the news. To mitigate this issue and to evaluate whether the results presented before extend beyond large firms with news coverage, we follow the multi-factor framework of Fama and French (1993, 2015) and calculate beta coefficients for each type of climate risk for *all* firms and not just those firms covered by the media. Specifically, we determine climate-risk betas by regressing individual stock returns on the returns of the GMB and the high-minus-low physical climate risk portfolio (PhysCR) defined before. Thus, we distinguish between regulatory climate-risk betas (β_{RegCR}) and physical climate-risk betas (β_{PhysCR}) in the following analysis.

In order to calculate the regulatory climate-risk betas, we extend the market model by our green-minus-brown (GMB) portfolio (regulatory climate-risk factor) (Equation (13)). Positive regulatory climate-risk betas indicate green firms while negative betas indicate brown firms. Similarly, we calculate physical climate risk betas according to Equation (14). In this case, we also control for size by including the SMB factor. This is necessary because we introduce a systematic bias towards small firms with the equal-weighted low physical climate-risk portfolio (the correlation coefficient with SMB is 0.649, see Table 6). Positive physical climate-risk betas indicate firms that are highly exposed to physical climate risks, i.e., storms, hurricanes, wildfires, droughts, etc., while firms with negative climate-risk betas have no or minor exposure to physical climate risks.[9]

$$R_{p,t} - R_{f,t} = a_p + \beta_p(R_{M,t} - R_{f,t}) + \beta_{RegCR,p} \times GMB_t + \epsilon_t \tag{13}$$

$$R_{p,t} - R_{f,t} = a_p + \beta_p(R_{M,t} - R_{f,t}) + \beta_{size,p} \times SMB_t + \beta_{PhysCR,p} \times PhysCR_t + \epsilon_t \tag{14}$$

4.4.1 Characteristics of Climate Risk Beta Sorted Portfolios

Again, we form climate-risk portfolios, this time however, we sort stocks based on their climate-risk betas. Every month we rank firms by their regulatory climate-risk beta

[9] The climate risk betas are calculated by regressing monthly excess stock returns (in excess to the risk free rate R_f) onto the returns of the factor models over a 72-month rolling window (at least 36 month of return data has to be available) with betas updated every month.

and form a "High Regulatory Climate Risk" portfolio ("Brown" portfolio) by selecting firms with betas in the first tercile and a "Low Regulatory Climate Risk" portfolio ("Green" portfolio) with betas in the third tercile. Similarly we form a "High Physical Climate Risk" portfolio by selecting firms with physical climate-risk betas in the third tercile and a "Low Physical Climate Risk" portfolio by selecting firms with betas in the first tercile. Figure 7 shows the cumulative returns of (a) value-weighted and (b) equal-weighted portfolios together with the market portfolio.

(a)

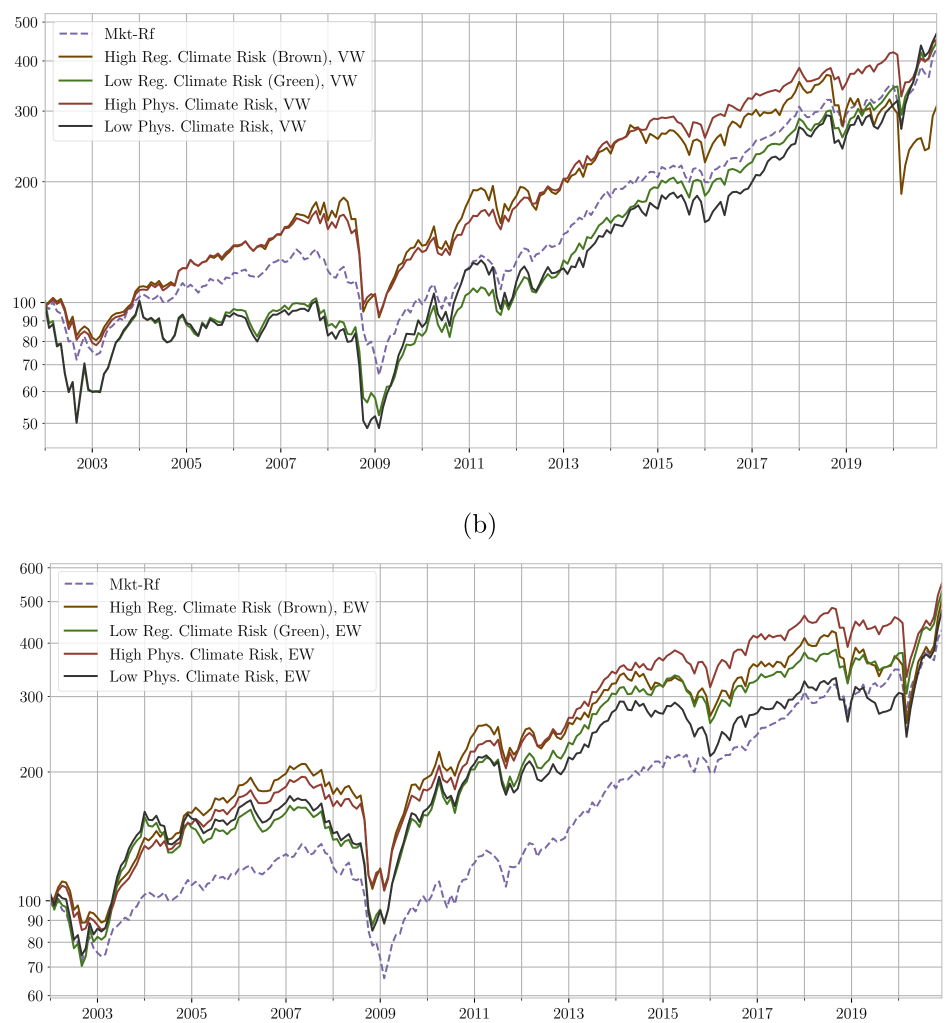


Figure 7: Cumulative returns of (a) value- and (b) equal-weighted climate risk beta sorted portfolios over the period Jan. 2002 to Dec. 2020. We sort stocks in a high- and low regulatory climate risk portfolio, as well as a high- and low physical climate risk portfolio.

In Table 8 we highlight the constituents of the beta sorted climate-risk portfolios that have the largest average portfolio weight over the period from Jan. 2002 to Dec. 2020. We observe that the top holdings of the "Green" portfolio are dominated by technology, telecommunications and software firms while the "Brown" portfolio is dominated by firms operating in the Oil and Gas sector.

The top holdings of the physical climate risk portfolio also include firms of the Oil and Gas sector like Exxon Mobil and Chevron next to insurance companies like American International Group and telecommunication firms like AT&T and Verizon Communications.[10]

Due to value weighting, portfolio weights are tilted towards large firms by construction. The cumulative weight of the 30 largest holdings is 30.47% for the "Brown" portfolio, 48.34% for the "Green" portfolio and 39.91% for the physical climate-risk portfolio. Big tech stocks like Apple, Microsoft, Amazon, etc. and large Oil and Gas producers like Exxon Mobil and Chevron receive large weights due to their high market caps. Note, that two technology companies, Apple and Meta Platforms, also appear in the "Brown" portfolio, which are likely misclassifications. In Appendix C we calculate beta-sorted portfolios by excluding all firms with a highly insignificant beta (t-value ≤ 1) and find that these firms vanish from the "Brown" portfolio.

We highlight the industries that are most exposed to the climate risk in Table 13 (see, Appendix A). The industries most exposed to regulatory climate risk are *Oil and Gas Extraction*, *Petroleum Refining and Related Industries* and *Electric, Gas, And Sanitary Services*. Among the industries less exposed to regulatory climate risk are the industries *Business Services*, *Electronic And Other Electrical Equipment* and *Industrial And Commercial Machinery And Computer Equipment*. Also, we find that the firms of the industries *Electric, Gas, And Sanitary Services*, *Chemicals And Allied Products* and *Insurance Carriers* are among the industries with the highest exposure to physical climate risk.

To alleviate the influence of the value weighting, we also calculate the top positions of equally weighted portfolios in Table 14 (see, Appendix B). As expected, the equally

[10] According to the Wireless Infrastructure Association there are 142,100 cellular towers and 209,500 macrocell sites in operation by telecommunication firms (Wireless Infrastructure Association, 2023). This type of infrastructure is highly exposed to physical climate risks such as storms and hurricanes.

weighted portfolios are less influenced by large technology companies.

	Regulatory Climate Risk (Brown) Portfolio			Physical Climate Risk Portfolio			Sustainability (Green) Portfolio		
	Weight (%)		Company Name	Weight (%)		Company Name	Weight (%)		Company Name
0	6.81	6.81	Exxon Mobil Corp	5.81	5.81	Exxon Mobil Corp	7.43	7.43	Microsoft Corp
1	3.11	9.92	Chevron Corp New	3.07	8.88	Johnson & Johnson	4.41	11.85	Intel Corp
2	2.02	11.94	Conocophillips	2.71	11.59	Chevron Corp New	4.09	15.94	Cisco Systems Inc
3	1.27	13.21	Eog Resources Inc	2.57	14.16	Walmart Inc	3.42	19.36	General Electric Co
4	1.19	14.40	Occidental Petroleum Corp	2.30	16.46	Coca Cola Co	2.92	22.28	Apple Inc
5	1.11	15.51	Apple Inc	2.11	18.57	Berkshire Hathaway Inc Del	2.87	25.15	Oracle Corp
6	1.08	16.59	Meta Platforms Inc	2.04	20.61	AT & T Inc	1.96	27.11	Amazon Com Inc
7	0.82	17.41	American International Group Inc	2.02	22.63	Procter & Gamble Co	1.77	28.88	Alphabet Inc
8	0.81	18.22	Coca Cola Co	1.67	24.30	Pepsico Inc	1.70	30.58	Berkshire Hathaway Inc Del
9	0.76	18.99	Devon Energy Corp New	1.65	25.94	Verizon Communications Inc	1.41	31.98	Dell Inc
10	0.72	19.70	Caterpillar Inc	1.20	27.15	General Electric Co	1.21	33.20	Walmart Inc
11	0.71	20.41	Halliburton Company	1.02	28.17	Mcdonalds Corp	1.14	34.34	Johnson & Johnson
12	0.67	21.08	Johnson & Johnson	1.01	29.18	Conocophillips	1.09	35.43	Qualcomm Inc
13	0.67	21.76	Procter & Gamble Co	0.84	30.02	Pfizer Inc	1.07	36.50	International Business Machs Cor
14	0.64	22.40	Valero Energy Corp New	0.81	30.83	Philip Morris International Inc	1.06	37.57	Comcast Corp New
15	0.63	23.03	Unitedhealth Group Inc	0.81	31.64	American International Group Inc	1.03	38.60	Amgen Inc
16	0.63	23.66	Exelon Corp	0.72	32.36	Bristol Myers Squibb Co	0.98	39.57	EMC Corp Ma
17	0.63	24.29	Berkshire Hathaway Inc Del	0.67	33.03	Intel Corp	0.97	40.54	Home Depot Inc
18	0.62	24.90	Philip Morris International Inc	0.64	33.67	Home Depot Inc	0.91	41.45	HP Inc
19	0.58	25.48	APA Corp	0.63	34.30	Unitedhealth Group Inc	0.80	42.26	Time Warner Inc New
20	0.56	26.04	Anadarko Petroleum Corp	0.62	34.92	3M Co	0.76	43.01	Pepsico Inc
21	0.53	26.57	Dominion Energy Inc	0.60	35.52	United Parcel Service Inc	0.73	43.74	Procter & Gamble Co
22	0.51	27.08	Hess Corp	0.60	36.12	Union Pacific Corp	0.63	44.37	Merck & Co Inc New
23	0.51	27.59	Southern Copper Corp	0.56	36.68	Altria Group Inc	0.62	44.98	Verizon Communications Inc
24	0.51	28.10	Freeport Mcmoran Inc	0.56	37.24	Southern Co	0.59	45.58	Yahoo Inc
25	0.49	28.59	Deere & Co	0.55	37.79	Costco Wholesale Corp New	0.57	46.14	Applied Materials Inc
26	0.49	29.08	Boeing Co	0.54	38.33	Merck & Co Inc New	0.57	46.71	Corning Inc
27	0.48	29.55	NOV Inc	0.53	38.86	Dominion Energy Inc	0.55	47.26	Bristol Myers Squibb Co
28	0.47	30.02	Baker Hughes Co	0.53	39.39	Duke Energy Corp New	0.55	47.81	Target Corp
29	0.45	30.47	Marathon Oil Corp	0.53	39.91	Exelon Corp	0.53	48.34	AT & T Inc

Table 8: Top 30 companies of the value weighted climate risk beta sorted regulatory climate risk (brown), physical climate risk and sustainability (green) portfolios. The weights are averages in %, calculated over the period Jan. 2002 to Dec. 2020.

4.4.2 Climate Risk Premia using Beta Sorted Portfolios

Analog to Section 4.2, we form a zero-investment portfolio that is long (short) the beta sorted "Green" ("Brown") portfolio. Figure 8 shows the cumulative returns of the equal- and value-weighted, beta sorted GMB portfolios.

We observe a downward trend for the GMB portfolio until 2011. This is followed by an upward trend that lasts until the end of the sample period. Since we use value weighting which is commonly used in the literature, we compare this result with two important results from the literature: Hsu et al. (2022) find that polluters outperform non-polluting companies while Pástor et al. (2022) reports a strong outperformance of green over brown stocks. We show that the authors obtain these contrary results as they focus on different sample periods.

While Hsu et al. (2022) consider the period 1991 to 2016, Pástor et al. (2022) analyze the period Nov. 2012 to Dec. 2020 which can be characterized by the rise of sustainable finance and growing availability of ESG data. Hsu et al. (2022) argue that brown stocks have higher realized returns because investors demand higher ex ante risk premia for high-emission firms as they carry a higher risk of being affected by policy-regime shifts towards a more environmentally-friendly economy. Pástor et al. (2022) also argues that brown firms have a higher risk premium and thus higher ex ante expected returns. However, the authors show that the strong performance of green stocks since 2012 is caused by unexpected windfall gains due to increased climate concerns and rising investor demand.

Given the longer time-series, compared to the literature, that we work with, we can contribute to the above discussion and provide more nuanced empirical evidence. Our findings suggest that these windfall gains surpassed the climate risk premium around 2012. The trend towards sustainable investing further contributed to an increased demand for green assets, resulting in positive returns for the GMB portfolio in 2012 and thereafter. The fact that the same pattern, albeit less pronounced, is observed in the equally weighted portfolio tells us that the outperformance of green versus brown stocks from 2011 onward is not only due to large technology stocks, but as conjectured due to a broad shift in investor demand towards sustainable businesses.

Moreover, in comparison to the topic-exposure weighted portfolio in Section 4.2, we do not observe a drawdown but only a sideways movement from 2015 to 2018 due to the broader coverage of the investment universe and the different weight distribution of the climate-risk-beta sorted portfolios. Also, note that the positive returns of the GMB portfolio are driven by an underperformance of brown stocks rather than an outperformance of green stocks relative to the market portfolio (see Figure 7). This also shows up in Table 7 (Model 5, subperiod 2) as the positive risk premium for sustainability (Sus) is smaller in absolute terms than the negative risk premium for regulatory climate risk (Reg).

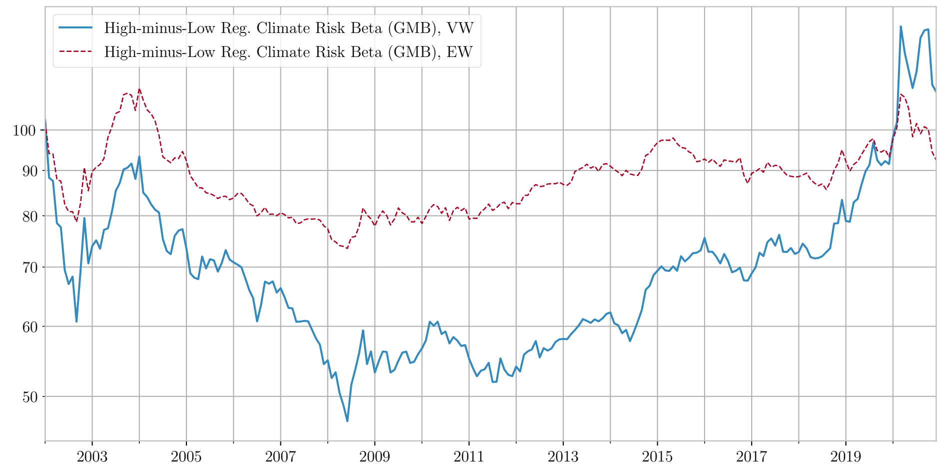


Figure 8: Cumulative returns of the value-weighted (VW) and equal-weighted (EW), beta sorted, green-minus-brown (GMB) portfolio over the period from Jan. 2002 to Dec. 2020.

We quantify the similarity between the news-exposure sorted GMB portfolio and the climate-risk-beta sorted GMB portfolio by calculating the correlation between the two time-series over the period Jan. 2002 to Dec. 2020. The resulting correlation coefficient is 0.67 for quarterly returns (0.54 for monthly- and 0.64 for annual returns). The high correlation coefficient shows that the broader beta-based approach is closely related to firm-specific climate risk characteristics extracted from news.

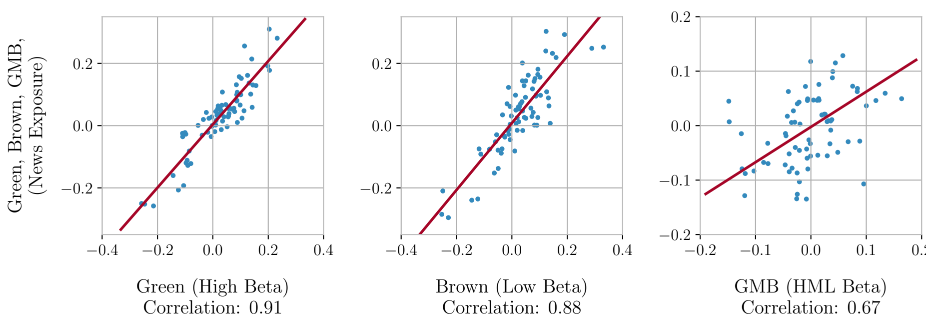


Figure 9: Correlation between the news exposure sorted and value-weighted beta sorted regulatory climate risk portfolios over the period Jan. 2002 to Dec. 2020 calculated on quarterly returns.

Next, we turn to physical climate risk. Figure 10 provides insights into the relative performance of the value-weighted and equal-weighted high-minus-low physical climate-risk portfolios. The equal-weighted portfolio shows a pattern similar to the topic-exposure weighted portfolio in Figure 6: an upward trend from 2011 to 2019 that ends with the start of the pandemic in 2020. This positive performance is also in line with the significant physical climate-risk premium reported in Table 7.

The value-weighted portfolio, on the other hand, is experiencing a sharp downturn after peaking at the end of 2008. This is due to the fact that large-cap technology firms, which experience exceptionally strong returns over the second half of the sample, are concentrated in the low physical climate risk portfolio. This exceeds the premium on physical climate risk and thus results in a negative performance.

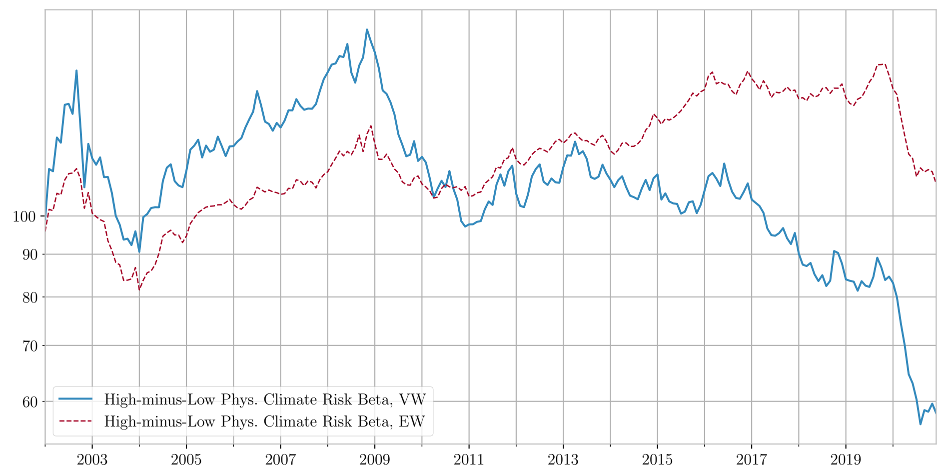


Figure 10: Cumulative returns of the value-weighted (VW) and equal-weighted (EW), beta sorted, high-minus-low physical climate risk beta portfolio over the period from Jan. 2002 to Dec. 2020.

Again, we quantify the similarity between the topic-exposure sorted and climate-beta sorted portfolios by calculating the correlation between the two time-series over the period Jan. 2002 to Dec. 2020. The resulting correlation coefficient is 0.63 for quarterly returns (0.52 for monthly and 0.74 for annual returns).

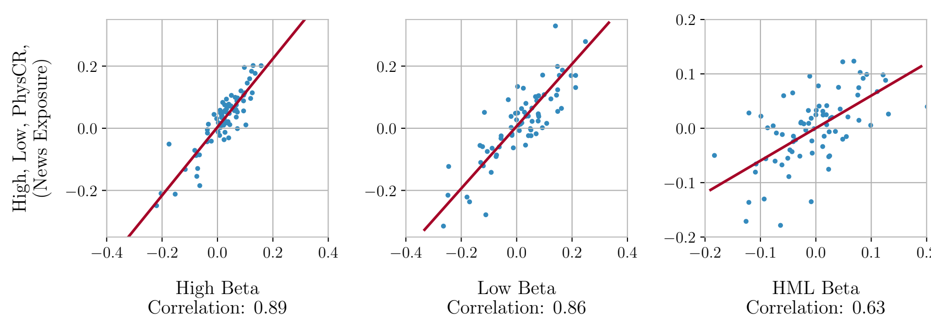


Figure 11: Correlation between the news exposure sorted and value-weighted beta sorted physical climate risk portfolios over the period Jan. 2002 to Dec. 2020 calculated on quarterly returns.

4.5 Validation

In this section, we pool complementary results that should provide additional validation to our news-based approach.

4.5.1 Comparison With an ESG-sorted GMB Portfolio

We further validate our methodology and results by comparing our beta-sorted GMB portfolio with the E-score-sorted GMB portfolio of Pástor et al. (2022). The authors use MSCI ESG ratings data to calculate firm-level environmental scores. Based on the calculated scores they form value-weighted portfolios by selecting the top third of firms with the highest environmental score (green portfolio) and the bottom third of firms with the lowest environmental score (brown portfolio).

The correlation between our beta-sorted GMB portfolio and the GMB portfolio of Pástor et al. (2022) is 0.64, calculated on the basis of quarterly returns (0.46 for monthly and 0.70 for annual returns) over the period Jan. 2009 to Dec. 2020 (see Figure 12). In addition, our "Green" and "Brown" portfolios have also a strong correlation of 0.92 with Pastor's respective "Green" and "Brown" portfolios based on quarterly returns. These high correlations indicate a high degree of similarity between the underlying portfolios. This can be observed when plotting the cumulative returns, as shown in Figure 13. Figure 13a shows the cumulative returns of the green, brown and the market portfolio, in comparison with the green and brown portfolio of Pástor et al. (2022). The cumulative returns of our "Green" and "Brown" portfolio (solid lines) align almost perfectly with the "Green" and "Brown" portfolio of Pástor et al. (2022) (dashed lines). Figure 13b plots the cumulative returns of the GMB portfolios. Again, the two portfolios tend to have a small tracking error. Only after 2018 this error increases moderately, as our "Brown" portfolio slightly underperforms the E-score-sorted portfolio.

The high degree of similarity between these portfolios is surprising as the underlying methodology for identifying green and brown companies is completely different. ESG scoring is an elaborate "bottom-up" approach that requires a thorough analysis of a company's operations, including key product/business segments, and calculations of exposures to key environmental risks. It also involves measurements of carbon intensity and emissions at the firm level.

Our approach, in contrast, can be seen as a "top-down" approach. Brown (green) firms have a higher chance of being mentioned in news that cover brown (green) topics. In addition, firms whose returns covary with the returns of these identified firms, as measured by the climate-risk beta, are most likely also exposed to the same risks. We argue that a simple metric such as our climate-risk beta, calculated in a similar way to the common risk factors available in the literature, can be used as an alternative to environmental scores to identify climate risks of individual companies.

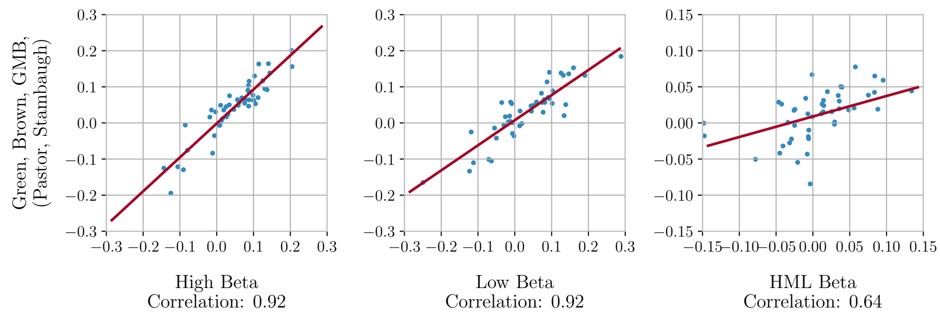
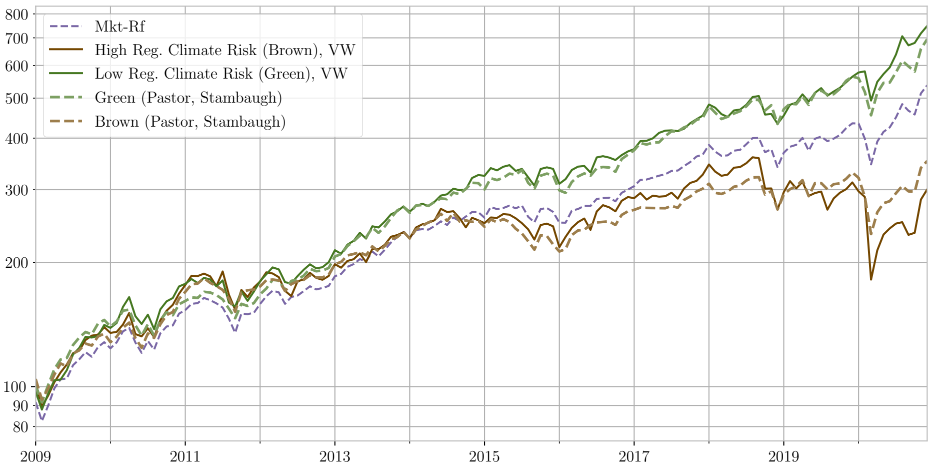


Figure 12: Correlation between the regulatory climate risk beta sorted green, brown and green-minus-brown (GMB) portfolio with the green, brown and GMB portfolio of Pástor et al. (2022) using quarterly returns over the period Jan. 2009 to Dec. 2020.

4.5.2 Exposure to Well-known Risk Factors

To assess to what extent the climate risk premia identified and discussed before are robust to existing empirical asset pricing models, we regress the returns of the value-weighted and equal-weighted GMB portfolio (Table 9) and the high-minus-low physical climate-risk portfolios (Table 10) on several well known risk factors documented by Fama and French (1993, 2015) and Carhart (1997). The explanatory variables are the market portfolio (Mk-Rf), size factor (SMB), value factor (HML), profitability (RMW), investment (CMA) and momentum (UMD). For each regression we show results for the full period ranging from Jan. 2002 to Dec. 2020 (Full) as well as for the two subperiods Jan. 2002 to Dec. 2011 (1) and Jan. 2012 to Dec. 2020 (2).

(a)



(b)

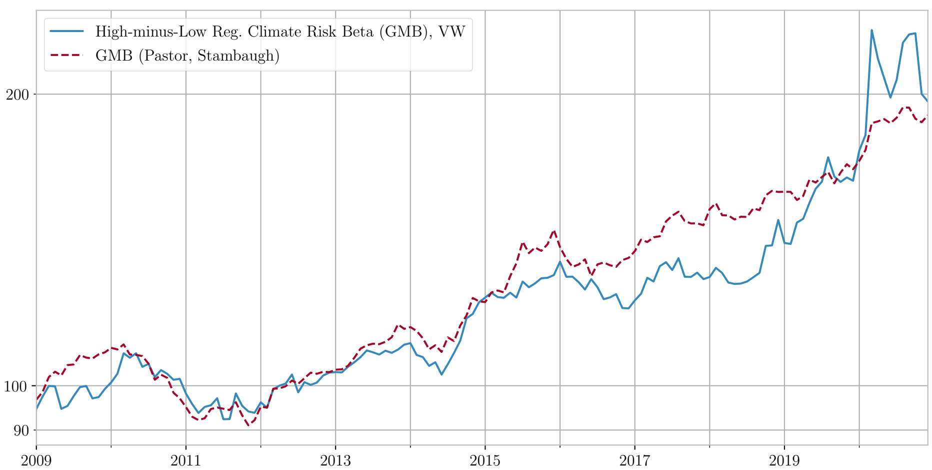


Figure 13: Cumulative returns of (a) the green (sustainability), brown (regulatory climate risk) portfolio and (b) the beta sorted green-minus-brown (GMB) portfolio over the period from Jan. 2009 to Dec. 2020.

Most importantly, we find a positive and significant alpha of 80 bps per month (9.60% p.a.) with a t-value of 2.80 for the value-weighted GMB portfolio from 2012 to 2020 (last column of Panel A in Table 9). Thus, the common risk factors are not able to fully explain the strong performance of the value-weighted GMB portfolio from 2012 onwards. For the equal-weighted GMB portfolio the alpha is only 18 bps per month (2.16% p.a.). However, with a t-value of 1.10 this alpha is insignificant. Furthermore, we observe that the explained variance R^2 is smaller for the full period than for each of the two subperiods. In Panel A, R^2 is 31.99% for the full sample, 39.31% for the first and 56.54% for the second subperiod. The low R^2 for the full period is a direct result of the regime shift in 2012. The difference between the two subperiods is also reflected in the coefficients. While for the first subperiod only the coefficient of RMW is significant, in the second subperiod Mkt-RF, SMB, HML and CMA are significant with a positive coefficient on CMA and negative coefficients on the market, SMB, and HML. For the equal-weighted portfolio in Panel B we get an R^2 of 33.28% for the full, 41.84% for the first and 45.35% for the second subperiod. In the first subperiod, the coefficients of HML, RMW and CMA are significant. For the second subperiod Mkt-RF, SMB, HML and RMW are significant.

For the equal-weighted high-minus-low physical climate risk portfolios we find an alpha of 16 bps per month (1.92% p.a.). However, with a t-value of 0.987 it is insignificant (last column of Panel A in Table 10). For the value-weighted portfolio the alpha is negative and insignificant.

Period	Full	1	2	Full	1	2	Full	1	2	Full	1	2
Panel A: Dependent Variable: VW GMB Portfolio												
Constant	0.0015	-0.0050	0.0139***	0.0007	-0.0052	0.0089***	0.0043*	0.0013	0.0082***	0.0044*	0.0008	0.0080***
	(0.5316)	(-1.2894)	(3.9576)	(0.2495)	(-1.3054)	(3.0711)	(1.7333)	(0.3763)	(2.9054)	(1.7529)	(0.2340)	(2.8041)
Mkt-RF	-0.0273	0.2641***	-0.5008***	0.0769	0.2712***	-0.3004***	-0.0569	-0.0643	-0.2401***	-0.0715	-0.1026	-0.2164***
	(-0.4230)	(3.1525)	(-6.0003)	(1.1352)	(2.9119)	(-4.1006)	(-0.9022)	(-0.6871)	(-3.1998)	(-1.0809)	(-1.0811)	(-2.7226)
SMB				-0.2525**	0.0567	-0.4960***	-0.4370***	-0.0879	-0.5767***	-0.4310***	-0.0420	-0.5542***
				(-2.1003)	(0.3279)	(-4.1363)	(-4.1121)	(-0.6008)	(-4.4300)	(-4.0402)	(-0.2858)	(-4.1794)
HML				-0.3407***	-0.1275	-0.5396***	-0.3665***	-0.0307	-0.6486***	-0.3897***	-0.0945	-0.6074***
				(-3.1102)	(-0.7798)	(-5.1626)	(-3.4444)	(-0.2096)	(-5.2550)	(-3.5107)	(-0.6329)	(-4.6170)
RMW							-1.0338***	-1.1860***	-0.3803*	-1.0110***	-1.0838***	-0.3751*
							(-7.8331)	(-6.7244)	(-1.9477)	(-7.4516)	(-5.9114)	(-1.9183)
CMA							0.4901***	0.2791	0.4393**	0.4912***	0.3078	0.4563**
							(2.8779)	(1.2518)	(2.0038)	(2.8815)	(1.3910)	(2.0721)
UMD										-0.0449	-0.1305*	0.0870
										(-0.7415)	(-1.8269)	(0.9110)
Observations	228	120	108	228	120	108	228	120	108	228	120	108
R^2	0.0008	0.0777	0.2535	0.0811	0.0826	0.5308	0.3182	0.3751	0.5618	0.3199	0.3931	0.5654
Adjusted R^2	-0.0036	0.0699	0.2465	0.0688	0.0589	0.5173	0.3029	0.3477	0.5403	0.3015	0.3608	0.5395
Residual Std. Error	0.0429	0.0428	0.0349	0.0413	0.0431	0.0280	0.0357	0.0359	0.0273	0.0358	0.0355	0.0273
F Statistic	0.1789	9.9385***	36.0030***	6.5873***	3.4819**	39.2178***	20.7260***	13.6878***	26.1537***	17.3283***	12.1967***	21.8967***
Panel B: Dependent Variable: EW GMB Portfolio												
Constant	-0.0000	-0.0016	0.0041**	-0.0005	-0.0020	0.0022	0.0014	0.0014	0.0018	0.0014	0.0014	0.0018
	(-0.0100)	(-0.7316)	(2.3072)	(-0.3118)	(-0.8953)	(1.3419)	(1.1017)	(0.7458)	(1.1598)	(1.0935)	(0.7105)	(1.1089)
Mkt-RF	-0.0100	0.1323***	-0.2303***	0.0316	0.1358***	-0.1396***	-0.0389	-0.0474	-0.1069**	-0.0370	-0.0518	-0.1006**
	(-0.2934)	(2.7922)	(-5.4429)	(0.8689)	(2.6325)	(-3.4207)	(-1.1753)	(-0.9364)	(-2.5727)	(-1.0672)	(-0.9940)	(-2.2785)
SMB				-0.0750	0.1242	-0.2666***	-0.1780***	0.0339	-0.3372***	-0.1787***	0.0392	-0.3312***
				(-1.1641)	(1.2964)	(-3.9908)	(-3.1971)	(0.4288)	(-4.6764)	(-3.1944)	(0.4860)	(-4.4953)
HML				-0.1785***	-0.2014**	-0.1622***	-0.2086***	-0.1677**	-0.1964***	-0.2057***	-0.1750**	-0.1855**
				(-3.0410)	(-2.2226)	(-2.7851)	(-3.7423)	(-2.1124)	(-2.8734)	(-3.5340)	(-2.1352)	(-2.5375)
RMW							-0.5681***	-0.6560***	-0.2852***	-0.5710***	-0.6443***	-0.2838**
							(-8.2175)	(-6.8717)	(-2.6377)	(-8.0250)	(-6.4031)	(-2.6131)
CMA							0.3297***	0.2534**	0.1787	0.3296***	0.2567**	0.1832
							(3.6965)	(2.0999)	(1.4716)	(3.6867)	(2.1137)	(1.4974)
UMD										0.0056	-0.0149	0.0231
										(0.1770)	(-0.3808)	(0.4358)
Observations	228	120	108	228	120	108	228	120	108	228	120	108
R^2	0.0004	0.0620	0.2184	0.0586	0.1042	0.4066	0.3327	0.4176	0.4525	0.3328	0.4184	0.4535
Adjusted R^2	-0.0040	0.0540	0.2111	0.0460	0.0810	0.3895	0.3177	0.3921	0.4256	0.3147	0.3875	0.4210
Residual Std. Error	0.0227	0.0242	0.0177	0.0221	0.0239	0.0156	0.0187	0.0194	0.0151	0.0188	0.0195	0.0152
F Statistic	0.0861	7.7966***	29.6255***	4.6475***	4.4968***	23.7538***	22.1349***	16.3504***	16.8572***	18.3705***	13.5473***	13.9677***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: We run monthly time-series regressions over the periods Jan. 2002 to Dec. 2020 (Full) as well as the two subperiods Jan. 2002 to Dec. 2011 (1) and Jan. 2012 to Dec. 2020 (2). In Panel A, the dependent variable is the value-weighted (VW) beta sorted green-minus-brown (GMB) portfolio. In Panel B, the dependent variable is the equal-weighted (EW) beta sorted GMB portfolio. Mkt-Rf is the excess market return, SMB is the size- and HML is the value factor of Fama and French (1993). RMW and CMA are the profitability and investment factors of Fama and French (2015) and UMD is the momentum factor of Carhart (1997).

Period	Full	1	2	Full	1	2	Full	1	2	Full	1	2
Panel A: Dependent Variable: VW High-minus-low Physical Climate Risk Portfolio												
Constant	0.0012	0.0035	-0.0031	0.0026	0.0039	-0.0001	-0.0014	-0.0022	-0.0008	-0.0015	-0.0017	-0.0014
	(0.5026)	(0.9596)	(-1.0315)	(1.1377)	(1.1048)	(-0.0400)	(-0.6549)	(-0.6793)	(-0.3161)	(-0.7405)	(-0.5403)	(-0.5875)
Mkt-RF	-0.3814***	-0.4850***	-0.2135***	-0.4257***	-0.5190***	-0.2673***	-0.2818***	-0.2159**	-0.2146***	-0.2402***	-0.1819**	-0.1546**
	(-7.0858)	(-6.2562)	(-2.9784)	(-7.7372)	(-6.2738)	(-3.8591)	(-5.3859)	(-2.5810)	(-3.3405)	(-4.4391)	(-2.1418)	(-2.3479)
SMB				-0.1140	-0.1746	-0.0781	0.0282	-0.0551	0.0918	0.0111	-0.0957	0.1487
				(-1.1683)	(-1.1367)	(-0.6887)	(0.3197)	(-0.4210)	(0.8238)	(0.1275)	(-0.7281)	(1.3535)
HML				0.5113***	0.4711***	0.5553***	0.3835***	0.3649***	0.2365**	0.4495***	0.4213***	0.3408***
				(5.7498)	(3.2440)	(5.6201)	(4.3465)	(2.7813)	(2.2378)	(4.9525)	(3.1538)	(3.1264)
RMW							0.8811***	1.0635***	0.3778**	0.8157***	0.9729***	0.3911**
							(8.0522)	(6.7417)	(2.2594)	(7.3525)	(5.9317)	(2.4140)
CMA							0.1520	-0.1532	0.9185***	0.1488	-0.1786	0.9615***
							(1.0770)	(-0.7684)	(4.8927)	(1.0676)	(-0.9024)	(5.2693)
UMD										0.1282**	0.1156*	0.2202***
										(2.5902)	(1.8087)	(2.7821)
Observations	228	120	108	228	120	108	228	120	108	228	120	108
R^2	0.1818	0.2491	0.0772	0.2878	0.3119	0.2973	0.4488	0.5247	0.4614	0.4650	0.5381	0.4997
Adjusted R^2	0.1782	0.2427	0.0685	0.2783	0.2941	0.2770	0.4364	0.5039	0.4350	0.4505	0.5135	0.4700
Residual Std. Error	0.0358	0.0396	0.0300	0.0335	0.0382	0.0264	0.0296	0.0321	0.0234	0.0293	0.0317	0.0226
F Statistic	50.2088***	39.1406***	8.8710***	30.1726***	17.5301***	14.6679***	36.1496***	25.1700***	17.4756***	32.0177***	21.9382***	16.8154***
Panel B: Dependent Variable: EW High-minus-low Physical Climate Risk Portfolio												
Constant	0.0011	0.0020	0.0000	0.0019	0.0024	0.0016	-0.0002	-0.0014	0.0020	-0.0003	-0.0013	0.0016
	(0.7845)	(0.9560)	(0.0133)	(1.4226)	(1.1607)	(0.9195)	(-0.1589)	(-0.7906)	(1.2004)	(-0.2131)	(-0.7177)	(0.9867)
Mkt-RF	-0.0676**	-0.0679	-0.0610	-0.0798**	-0.0749	-0.0767*	-0.0022	0.1206**	-0.1114**	0.0147	0.1298***	-0.0744*
	(-2.1160)	(-1.4952)	(-1.3448)	(-2.4310)	(-1.5339)	(-1.7241)	(-0.0708)	(2.6079)	(-2.5863)	(0.4627)	(2.7349)	(-1.6756)
SMB				-0.1245**	-0.1396	-0.1135	-0.0314	-0.0555	0.0301	-0.0383	-0.0665	0.0652
				(-2.1396)	(-1.5403)	(-1.5582)	(-0.6123)	(-0.7673)	(0.4036)	(-0.7483)	(-0.9053)	(0.8803)
HML				0.2945***	0.2454***	0.3386***	0.2712***	0.1888**	0.3105***	0.2979***	0.2041***	0.3748***
				(5.5515)	(2.8626)	(5.3327)	(5.2835)	(2.6029)	(4.3836)	(5.5975)	(2.7334)	(5.0997)
RMW							0.5428***	0.6911***	0.5057***	0.5164***	0.6666***	0.5139***
							(8.5279)	(7.9236)	(4.5130)	(7.9393)	(7.2701)	(4.7055)
CMA							-0.1172	-0.1618	-0.0351	-0.1185	-0.1687	-0.0086
							(-1.4272)	(-1.4671)	(-0.2793)	(-1.4500)	(-1.5242)	(-0.0703)
UMD										0.0518*	0.0314	0.1357**
										(1.7862)	(0.8779)	(2.5431)
Observations	228	120	108	228	120	108	228	120	108	228	120	108
R^2	0.0194	0.0186	0.0168	0.1390	0.0880	0.2279	0.3662	0.4471	0.3565	0.3752	0.4509	0.3952
Adjusted R^2	0.0151	0.0103	0.0075	0.1275	0.0644	0.2056	0.3519	0.4229	0.3249	0.3582	0.4217	0.3593
Residual Std. Error	0.0212	0.0232	0.0190	0.0200	0.0226	0.0170	0.0172	0.0177	0.0157	0.0172	0.0177	0.0153
F Statistic	4.4775**	2.2357	1.8085	12.0559***	3.7325**	10.2325***	25.6513***	18.4394***	11.2995***	22.1188***	15.4637***	10.9989***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: We run monthly time-series regressions over the periods Jan. 2002 to Dec. 2020 (Full) as well as the two subperiods Jan. 2002 to Dec. 2011 (1) and Jan. 2012 to Dec. 2020 (2). In Panel A, the dependent variable is the value-weighted (VW) beta sorted high-minus-low physical climate risk portfolio. In Panel B, the dependent variable is the equal-weighted (EW) beta sorted high-minus-low physical climate risk portfolio. Mkt-Rf is the excess market return, SMB is the size- and HML is the value factor of Fama and French (1993). RMW and CMA are the profitability and investment factors of Fama and French (2015) and UMD is the momentum factor of Carhart (1997).

4.5.3 Climate Risk Factors

In Section 4.5.2 we show that the Fama-French factor models are not able to explain the outperformance of the green-minus-brown (GMB) portfolio from 2012 to 2020. Consequently, we now test whether the climate-risk factor portfolios, the regulatory climate-risk beta-sorted GMB portfolio as well as the high-minus-low physical climate-risk beta portfolio (PhysCR) are able to improve the explainability of average returns beyond the well-known factor models of Fama and French (1993, 2015). Similar to Fama and French (2015), we test how well the different factor models explain monthly excess returns $(r_i - r_f)$ of 25 Size-B2M, 25 Size-OP, 25 Size-Inv portfolios as well as 10 sector and 72 industry portfolios using the linear regression

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \tilde{r}_{P,t} + \tilde{\eta}_{i,t}, \qquad \forall_i = 1, ..., N, \tag{15}$$

estimated over a period of $t = 1, ..., T$ month. $\tilde{r}_{P,t} = (\tilde{r}_{1,t}, \tilde{r}_{2,t}, ..., \tilde{r}_{L,t})'$ denotes the return vector of the L factor portfolios that enter the market-model (Mkt-Rf), the three-factor model (FF3), the five-factor model (FF5) and an extension of each by our GMB and PhysCR portfolios. The ideal factor model that is able to fully explain expected returns has intercepts that are indistinguishable from zero (Fama and French, 2015). Consequently, we test whether the alphas for each set of 25, 10 or 72 time-series regressions are jointly zero by applying the GRS-test (Gibbons et al., 1989) under the null hypothesis

$$H_0 : \alpha_i = 0, \qquad \forall_i = 1, ..., N. \tag{16}$$

The GRS test statisitic W is calculated as follows:

$$\tilde{W} \equiv \frac{T(T-N-L)}{N(T-L-1)} \, \frac{\alpha \hat{\Sigma}^{-1} \hat{\alpha}'}{1 + \bar{R}_P \, \hat{\Omega}^{-1} \bar{R}_P'} \quad \sim \quad F_{N,T-N-L}, \tag{17}$$

with the factor return matrix $\tilde{R}_P = (\tilde{r}_{P,1}, ..., \tilde{r}_{P,T})'$, the variance-covariance matrix Ω and the variance-covariance matrix of the disturbances $\hat{\Sigma}$ given by

$$\Omega = \frac{1}{T}(\tilde{R}_P - \mathbf{1}\bar{R}_P)'(\tilde{R}_P - \mathbf{1}\bar{R}_P), \tag{18}$$

$$\hat{\Sigma} = \frac{\eta' \eta}{T - L - 1}. \tag{19}$$

$\bar{R}_P \equiv \frac{1}{T}\sum_{t=1}^{T} \tilde{R}_{P,t}$ is a $1 \times L$ vector of factor means, $\mathbf{1}$ is a T-dimensional column vector filled with ones and $\eta \in \mathbb{R}^{T \times N}$ is the residual matrix $(\eta_1, \eta_2, ..., \eta_N)$. Finally the p-value of the GRS-test is calculated as

$$p\text{-value} = 1 - F(\tilde{W},\, N,\, T\text{–}N\text{–}L), \tag{20}$$

with the cumulative distribution function F evaluated at $\tilde{W}$. The results of the GRS-test are shown in Table 12 and 11 for regressions performed over (1) the full period from Jan. 2002 to Dec. 2020 and (2) from Jan. 2012 to Dec. 2020. In addition to the GRS test statistic and its p-value we also report the average absolute value of the regression intercept $\|\alpha\| = \frac{1}{N}\sum_{i=1}^{N}\|\alpha_i\|$ and the associated t-value, which we calculate as follows: We take the unbiased estimator for the residual variance $\hat{\sigma}_i^2 = diag(\hat{\Sigma})_i$ and the fist element d_0 of $d = diag((\tilde{R}_P'\,\tilde{R}_P)^{-1})$ to calculate z_i (see Equation (21)). Then we calculate the average t-value according to Equation (22),

$$z_i \;=\; \frac{\alpha_i}{\hat{\sigma}_i\sqrt{d_0}} \quad\sim\quad t_{T-L-1}, \tag{21}$$

$$t\text{-value} \;=\; \frac{1}{N}\sum_{i=1}^{N}\|z_i\|. \tag{22}$$

We find that adding the GMB factor to the Fama-French 5-factor model (FF5) leads to a better model, as we observe a reduction in the GRS statistic in all cases (see Table 12 and 11). Consider the case of 72 industry portfolios in Panel E over the period (2): Extending the Fama-French 5-factor model (FF5) by the GMB portfolio results in a reduction of the GRS statistic from 2.44 to 1.38 and in an increase of the associated p-value from 0.0027 to 0.158. Thus, while we reject H_0 – all intercepts are jointly zero – for the five-factor model, we cannot reject H_0 after adding GMB. This is also true for the three-factor- (FF3) and the market model (Mkt-Rf).

For PhysCR, the effect is not as consistent: we observe a small reduction in the GRS statistic in some cases, but also worse results in others. An improvement can be observed for sector portfolios (Panel D) where the test statistic is further reduced if we add both, the GMB and the PhysCR factor. In period (2), the FF5 model has a GRS statistic of 1.999 with is lowered to 1.247 after adding the GMB portfolio. When we extend the FF5 model by both, GMB and PhysCR, we obtain a GRS statistic of 1.239. Similar improvements can be observed for the three-factor- (FF3) and the market model (Mkt-Rf).

These results show that the inclusion of climate-risk factors substantially increases the explainability of variations in asset returns, especially since 2012. In Panel A to C, for 25 Size-B2M/OP/INV sorted portfolios we observe similar results.

	(1) Full Period: Jan. 2002 to Dec. 2020				(2) Period: Jan. 2012 to Dec. 2020			
	GRS	$\|\alpha\|$ (%)	p-val. (GRS)	t-value	GRS	$\|\alpha\|$ (%)	p-val. (GRS)	t-value
Panel D: 10 Sector portfolios								
Mkt-Rf	1.1352	0.2192	0.3371	1.0506	2.3902	0.4562	0.014	1.3785
Mkt-Rf+GMB	1.1266	0.1918	0.3434	0.9766	1.0451	0.2424	0.4124	0.8245
Mkt-Rf+PhysCR	1.3818	0.2393	0.1901	1.1641	2.2471	0.4454	0.021	1.4069
Mkt-Rf+GMB+PhysCR	1.2722	0.2013	0.2476	1.0058	1.0346	0.245	0.4209	0.8713
FF3	0.9397	0.151	0.4976	0.7955	1.7691	0.352	0.0768	1.2351
FF3+GMB	0.9616	0.1459	0.4781	0.7886	1.1006	0.2411	0.3699	0.8851
FF3+PhysCR	1.1089	0.1799	0.3566	0.8941	1.7503	0.3519	0.0809	1.2654
FF3+GMB+PhysCR	0.9685	0.1398	0.472	0.7344	1.0809	0.2407	0.3849	0.9326
FF5	1.0931	0.2133	0.3687	0.9579	1.9986	0.3557	0.0421	1.2942
FF5+GMB	0.8411	0.1563	0.5896	0.7923	1.2467	0.2462	0.2726	0.9521
FF5+PhysCR	1.0543	0.2001	0.3993	0.9363	1.9906	0.3581	0.0431	1.3125
FF5+GMB+PhysCR	0.8772	0.1592	0.5554	0.8126	1.2389	0.2431	0.2774	0.9692
Panel E: 72 Industry portfolios								
Mkt-Rf	2.4765	0.2833	0.0	0.8488	2.6385	0.5034	0.0008	1.1386
Mkt-Rf+GMB	2.5458	0.2707	0.0	0.836	1.1576	0.2958	0.3183	0.677
Mkt-Rf+PhysCR	2.5259	0.2891	0.0	0.8826	2.3521	0.4804	0.0028	1.1102
Mkt-Rf+GMB+PhysCR	2.4044	0.2662	0.0	0.8381	1.2113	0.2951	0.2681	0.6873
FF3	2.5421	0.2653	0.0	0.8014	2.2481	0.3565	0.0046	0.8228
FF3+GMB	2.6513	0.263	0.0	0.8129	1.398	0.2974	0.1398	0.7049
FF3+PhysCR	2.3929	0.2638	0.0	0.7965	2.1963	0.3567	0.0062	0.8369
FF3+GMB+PhysCR	2.2247	0.2443	0.0	0.7596	1.4253	0.294	0.1292	0.7091
FF5	2.2793	0.2967	0.0	0.8678	2.4352	0.3505	0.0027	0.8265
FF5+GMB	2.1729	0.2759	0.0	0.8258	1.3754	0.3023	0.158	0.7283
FF5+PhysCR	2.2959	0.2973	0.0	0.8808	2.4314	0.3546	0.0031	0.8464
FF5+GMB+PhysCR	2.1677	0.2717	0.0	0.8181	1.4034	0.2969	0.1462	0.7259

Table 11: Continuation of Table 12. Panel D shows the GRS statistics for 10 sector portfolios and Panel E for 72 industry portfolios according to the SIC classification scheme. Using the GRS-test we test whether the alphas for each set of 10 or 72 time-series regressions are jointly zero. The table shows the GRS test statistic and its p-value together with the average absolute value of the intercepts $\|\alpha\|$ and its associated t-value.

	(1) Full Period: Jan. 2002 to Dec. 2020				(2) Period: Jan. 2012 to Dec. 2020			
	GRS	$\|\alpha\|$ (%)	p-val. (GRS)	t-value	GRS	$\|\alpha\|$ (%)	p-val. (GRS)	t-value
Panel A: 25 Size-B2M portfolios								
Mkt-Rf	1.554	0.193	0.0517	1.1592	1.322	0.4444	0.1743	1.7047
Mkt-Rf+GMB	1.508	0.1662	0.0646	1.0171	0.9839	0.1177	0.4971	0.4895
Mkt-Rf+PhysCR	1.6163	0.1948	0.0379	1.2152	1.245	0.3885	0.2286	1.5357
Mkt-Rf+GMB+PhysCR	1.5764	0.1692	0.0464	1.0869	0.9718	0.1176	0.5123	0.5038
FF3	1.7537	0.1135	0.0186	0.9971	1.2062	0.134	0.2607	0.8241
FF3+GMB	1.7326	0.1109	0.0209	0.9796	1.0169	0.1175	0.4571	0.7132
FF3+PhysCR	1.7503	0.1162	0.019	1.0459	1.1912	0.1321	0.2741	0.8202
FF3+GMB+PhysCR	1.6849	0.1099	0.0268	0.9934	1.0058	0.1174	0.4707	0.7198
FF5	1.362	0.0997	0.1261	0.9291	1.3062	0.1385	0.1863	0.8749
FF5+GMB	1.2433	0.0914	0.2059	0.8523	1.0939	0.1171	0.3701	0.7349
FF5+PhysCR	1.3502	0.0965	0.1328	0.9033	1.2866	0.1358	0.2001	0.869
FF5+GMB+PhysCR	1.2508	0.0932	0.2	0.8795	1.08	0.1171	0.3854	0.7413
Panel B: 25 Size-OP portfolios								
Mkt-Rf	0.9363	0.1331	0.5551	0.8323	1.3392	0.3734	0.1637	1.4663
Mkt-Rf+GMB	1.0581	0.1242	0.3947	0.8228	0.8839	0.0885	0.6248	0.4085
Mkt-Rf+PhysCR	0.9693	0.1331	0.51	0.8381	1.282	0.3378	0.2013	1.3197
Mkt-Rf+GMB+PhysCR	1.0178	0.1174	0.4457	0.7959	0.8809	0.0884	0.6286	0.4114
FF3	1.2149	0.0974	0.2294	0.8782	1.4065	0.1177	0.1285	0.7121
FF3+GMB	1.2561	0.1033	0.1956	0.9666	1.0942	0.0891	0.369	0.5637
FF3+PhysCR	1.1848	0.0903	0.2568	0.8333	1.4285	0.1188	0.1187	0.7189
FF3+GMB+PhysCR	1.1515	0.094	0.2896	0.8931	1.1084	0.0891	0.3544	0.5652
FF5	0.984	0.0831	0.4903	0.7965	1.4002	0.117	0.1326	0.7622
FF5+GMB	0.9009	0.0789	0.6041	0.7784	1.1044	0.0871	0.3589	0.584
FF5+PhysCR	0.9974	0.0835	0.4724	0.803	1.4318	0.1192	0.1182	0.7776
FF5+GMB+PhysCR	0.893	0.0778	0.6149	0.7703	1.1248	0.0867	0.3382	0.5833
Panel C: 25 Size-Inv portfolios								
Mkt-Rf	1.7634	0.1301	0.0176	0.8195	1.1976	0.3624	0.2672	1.4911
Mkt-Rf+GMB	1.7836	0.1184	0.0158	0.7598	1.0721	0.1032	0.3926	0.4901
Mkt-Rf+PhysCR	1.7527	0.1306	0.0187	0.831	1.1333	0.3204	0.3278	1.3054
Mkt-Rf+GMB+PhysCR	1.7787	0.1131	0.0163	0.7618	1.0633	0.1034	0.4027	0.5042
FF3	2.2432	0.1046	0.0011	1.0338	1.3354	0.1161	0.167	0.7832
FF3+GMB	2.2194	0.1092	0.0013	1.0883	1.2211	0.1021	0.2486	0.686
FF3+PhysCR	2.2059	0.0982	0.0014	0.9771	1.3408	0.1192	0.1643	0.8153
FF3+GMB+PhysCR	2.1245	0.1031	0.0023	1.0324	1.2139	0.1022	0.255	0.6982
FF5	1.7219	0.0793	0.0221	0.8469	1.6176	0.1276	0.0565	0.917
FF5+GMB	1.5889	0.0795	0.0438	0.8465	1.3443	0.1037	0.1632	0.7396
FF5+PhysCR	1.7063	0.0796	0.0241	0.8521	1.6409	0.1312	0.0518	0.9469
FF5+GMB+PhysCR	1.5928	0.0789	0.043	0.843	1.3533	0.103	0.1586	0.7422

Table 12: Summary statistics for GRS (Gibbons et al., 1989) tests of the market-, three-factor-, five-factor model and an extension of each by our regulatory- and physical climate risk factors (GMB and PhysCR) over (1) the full period from Jan. 2002 to Dec. 2020 (228 month) and (2) the period Jan. 2012 to Dec. 2020 (108 month). We test the ability of the various factor models to explain monthly excess returns on 25 Size-B2M portfolios (Panel A), 25 Size-OP portfolios (Panel B), 25 Size-Inv portfolios (Panel C). Using the GRS-test we test whether the alphas for each set of 25 time-series regressions are jointly zero. The table shows the GRS test statistic and its p-value together with the average absolute value of the intercepts $\|\alpha\|$ and its associated t-value.

4.5.4 Do Climate Betas Predict Future News Flow?

If the climate beta correctly identifies green and brown firms we would assume that companies with a high (low) regulatory climate-risk beta, i.e., green (brown) companies, are linked to future news articles of these topic. Similarly, we would assume that firms with a high physical climate-risk beta are also affected by future realizations of this climate risk.

To test if this is the case we regress the future (log-transformed) topic exposure onto the climate betas. Therefore we measure the firm-specific exposures to the sustainability topic $\bar{E}_{k=1,p}$ and the exposures to the regulatory climate risk topic $\bar{E}_{k=2,p}$ over 24 month from t to $t+24$, see Equation (23). As the topic exposure is a highly skewed variable – with several firms having high exposure while many have very low to no exposure – we log-transform the data as before. For regulatory climate risk, we regress the difference in the exposures on the sustainability and the regulatory climate-risk topic ($\bar{E}_{t,1,p} - \bar{E}_{t,2,p}$) on the regulatory climate-risk beta, see Equation (24). Similarly, for physical climate risk, we regress the firm-specific exposures to the physical climate-risk topic $\bar{E}_{k=3,p}$ on the physical climate-risk beta (Equation (25)).

As the climate betas $\beta_{RegCR,t,p}$ and $\beta_{PhysCR,t,p}$ are re-estimated on a monthly frequency, we also run the regression in a monthly interval from Jan. 2002 to Dec. 2018. The resulting coefficient b of the regression and its t-values are shown in Figure 14. We observe that the regression coefficients are almost always positive, indicating a positive relationship between the climate beta and future news content. The average value of b (t-value) is 0.073 (3.63) for regulatory climate risk and 0.168 (5.79) for physical climate risk. This implies that firms with a positive climate-risk beta are more likely affected by the consequences of climate change in the future.

$$\bar{E}_{t,k,p} = log\left(1 + \sum_{t}^{t+24} \bar{I}_{t,k,p}\right) \tag{23}$$

$$\bar{E}_{t,1,p} - \bar{E}_{t,2,p} = a_t + b_t \times \beta_{RegCR,t,p} + \epsilon_{t,p} \tag{24}$$

$$\bar{E}_{t,3,p} = a_t + b_t \times \beta_{PhysCR,t,p} + \epsilon_{t,p} \tag{25}$$

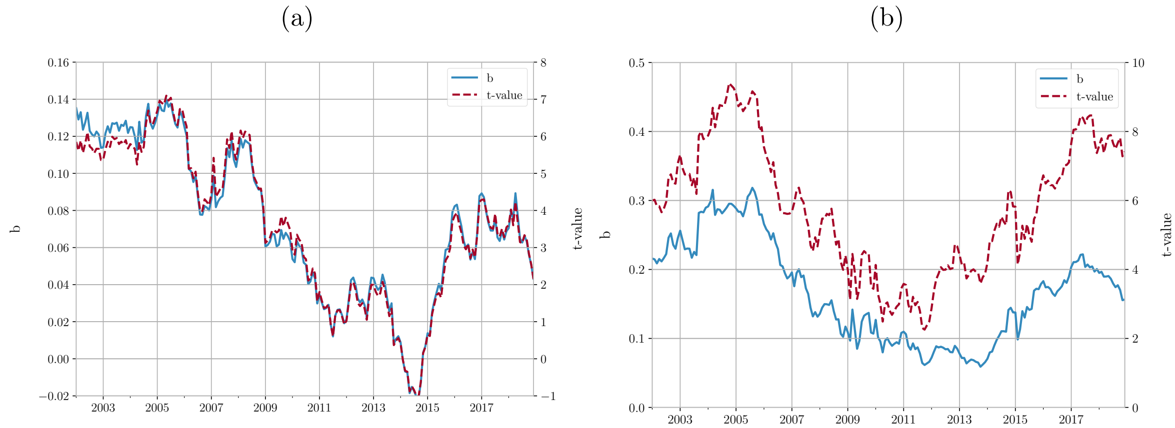


Figure 14: Coefficient b of the regressions shown in Formula 24 and 25 plotted together with the t-value over the period Jan. 2002 to Dec. 2018 for (a) the regulatory climate risk beta (β_{RegCR}) and (b) the physical climate risk beta (β_{PhysCR})

5 Conclusion

In this study, we propose a fully data-driven methodology to estimate firm-specific climate risk from public news. By utilizing a comprehensive dataset of almost 5 million U.S. news articles, we gain extensive support in the data to estimate the physical and regulatory climate risks for a wide range of U.S. stocks.

Our first main empirical finding is that we are the first to document a significant and economically sizable positive risk premium of 1.5% p.a. for physical climate risk over the period 2002 to 2020. This result is also robust to sector- and industry fixed effects indicating the risk exposure is at the individual firm-level.

Our second main result contributes to the ongoing discussion in the literature about the risk premium associated with regulatory climate risk. A portfolio that is long "green" stocks (low regulatory risk and good sustainability performance) and short "brown" stocks (high regulatory risk) reveals a regime shift occurring around 2012. The regulatory risk premium is positive from 2002 to 2012 (1.54% p.a.), but switches sign in the subsequent period from 2012 to 2020 becoming significantly negative with a point estimate of -2.56%. Thus, we contribute to the ongoing controversy in the literature about the sign of the regulatory climate risk premium as we are able to document this regime shift in a consistent framework. This is due to the use of news data that allows us to estimate firm-specific climate risk exposures back to 2002, while traditional data sources such as ESG datasets only start in the 2010s.

Methodologically, we apply a novel machine-learning technique to identify topic clusters in unstructured text, called Guided Topic Modeling. We furthermore extend the firm-specific news-based climate-risk estimates to a universe of 9000 U.S. equities by calculating physical and regulatory climate-risk betas. When forming climate-risk portfolios as before, but sorting stocks by their climate-risk betas, we observe very similar patterns in the return series indicating that climate-risk betas are useful and informative proxies of individual firms' exposures to regulatory and physical climate risks.

Finally, a comparison between our climate-beta sorted GMB portfolio and the ESG-sorted GMB portfolio of Pástor et al. (2022) shows a surprisingly high similarity in realized excess returns, yielding a correlation coefficient of 0.64. This adds validity to the proposed methodology and our results. It also suggests that news-based proxies, representing a top-down approach that only requires news as input, might be feasible, cost-effective alternative measures of company-specific climate risks compared to bottom-up ESG-scores with extensive data requirements.

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Appendices

A Industry Exposure of Climate Risk Beta Sorted Portfolios

	W (%)		(a) Reg. Climate Risk	W (%)		(b) Phys. Climate Risk	W (%)		(c) Sustainability
0	13.08	13.08	Oil And Gas Extraction	9.03	9.03	Electric, Gas, And Sanitary Services	19.81	19.81	Business Services
1	10.30	23.38	Petroleum Refining And Related Industries	8.90	17.93	Chemicals And Allied Products	14.55	34.36	Electronic And Other Electrical Equipment And ...
2	7.86	31.23	Electric, Gas, And Sanitary Services	7.97	25.90	Insurance Carriers	13.18	47.54	Industrial And Commercial Machinery And Comput...
3	6.15	37.38	Insurance Carriers	7.63	33.53	Petroleum Refining And Related Industries	8.97	56.51	Chemicals And Allied Products
4	5.84	43.22	Chemicals And Allied Products	6.77	40.30	Food And Kindred Products	4.74	61.25	Communications
5	5.60	48.82	Industrial And Commercial Machinery And Comput...	4.62	44.92	Measuring, Analyzing, And Controlling Instrume...	3.91	65.17	Measuring, Analyzing, And Controlling Instrume...
6	4.73	53.54	Automotive Dealers And Gasoline Service Stations	4.55	49.46	Oil And Gas Extraction	3.56	68.73	Insurance Carriers
7	4.45	58.00	Business Services	4.12	53.59	Automotive Dealers And Gasoline Service Stations	3.32	72.05	General Merchandise Stores
8	3.75	61.74	Transportation Equipment	4.04	57.63	General Merchandise Stores	2.86	74.91	Food And Kindred Products
9	3.18	64.93	Measuring, Analyzing, And Controlling Instrume...	3.74	61.37	Industrial And Commercial Machinery And Comput...	2.14	77.05	Building Materials, Hardware, Garden Supply, A...
10	3.04	67.96	Food And Kindred Products	3.30	64.67	Business Services	1.82	78.87	Transportation Equipment
11	2.14	70.10	Electronic And Other Electrical Equipment And ...	3.07	67.74	Communications	1.54	80.41	Engineering, Accounting, Research, Management,...
12	2.13	72.23	Tobacco Products	2.79	70.53	Tobacco Products	1.54	81.95	Apparel And Accessory Stores
13	1.97	74.20	Railroad Transportation	2.69	73.22	Transportation Equipment	1.35	83.29	Miscellaneous Retail
14	1.65	75.84	Nonclassifiable Establishments	2.33	75.55	Engineering, Accounting, Research, Management,...	1.26	84.56	Tobacco Products
15	1.61	77.45	Metal Mining	1.88	77.43	Railroad Transportation	1.10	85.66	Home Furniture, Furnishings, And Equipment Stores
16	1.42	78.87	Primary Metal Industries	1.86	79.29	Transportation By Air	1.00	86.66	Hotels, Rooming Houses, Camps, And Other Lodgi...
17	1.41	80.28	Wholesale Trade-durable Goods	1.77	81.07	Electronic And Other Electrical Equipment And ...	1.00	87.66	Transportation By Air
18	1.27	81.55	Communications	1.66	82.73	Eating And Drinking Places	0.98	88.64	Eating And Drinking Places
19	1.26	82.80	Fabricated Metal Products, Except Machinery An...	1.27	84.00	Building Materials, Hardware, Garden Supply, A...	0.97	89.61	Stone, Clay, Glass, And Concrete Products

Table 13: Top 20 industries of the climate risk beta sorted (a) regulatory climate risk, (b) physical climate risk and (c) sustainability portfolio calculated over the period Jan. 2002 to Dec. 2020. Industry exposures are calculated by summing up the monthly portfolio weights of each company over the period 2002 to 2020 and aggregating the weights at the industry level. To adjust for different industry sizes, in terms of industry firm count, we normalize the aggregate industry exposure by $(1+log(industry size))$. We use the logarithm to avoid overly penalizing large industries.

B Equal-Weighted Portfolios

	Regulatory Climate Risk (Brown) Portfolio			Physical Climate Risk Portfolio			Sustainability (Green) Portfolio		
	Weight (%)		Company Name	Weight (%)		Company Name	Weight (%)		Company Name
0	0.08	0.08	Seacor Holdings Inc	0.08	0.08	PNM Resources Inc	0.08	0.08	Best Buy Company Inc
1	0.08	0.16	Carbo Ceramics Inc	0.08	0.16	MDU Resources Group Inc	0.08	0.16	Cisco Systems Inc
2	0.08	0.25	Talos Energy Inc	0.08	0.25	UGI Corp New	0.08	0.25	Superconductor Technologies Inc
3	0.08	0.33	Universal Stnless & Aly Prods In	0.08	0.33	Firstenergy Corp	0.08	0.33	Intel Corp
4	0.08	0.41	Carrizo Oil & Gas Inc	0.08	0.41	Pricesmart Inc	0.08	0.40	Powerfleet Inc
5	0.08	0.49	Willbros Group Inc Del	0.08	0.49	Selective Insurance Group Inc	0.08	0.48	Alpha Pro Tech Ltd
6	0.08	0.57	Commercial Metals Co	0.08	0.58	J & J Snack Foods Corp	0.08	0.56	Cumulus Media Inc
7	0.08	0.66	Ion Geophysical Corp	0.08	0.66	Chevron Corp New	0.08	0.64	Repligen Corp
8	0.08	0.74	Team Inc	0.08	0.74	Idacorp Inc	0.08	0.71	Extreme Networks Inc
9	0.08	0.82	Cleveland Cliffs Inc New	0.08	0.82	Northwest Natural Holding Co	0.08	0.79	Innodata Inc
10	0.08	0.90	TRC Companies Inc	0.08	0.90	WGL Holdings Inc	0.08	0.86	Option Care Health Inc
11	0.08	0.98	Bristow Group Inc	0.08	0.99	Brady Corp	0.07	0.94	Broadvision Inc
12	0.08	1.06	United States Steel Corp New	0.08	1.07	Southwest Gas Holdings Inc	0.07	1.01	Sandisk Corp
13	0.08	1.14	Murphy Oil Corp	0.08	1.15	Black Hills Corp	0.07	1.09	Tivo Inc
14	0.08	1.22	PDC Energy Inc	0.08	1.23	RLI Corp	0.07	1.16	Windtree Therapeutics Inc
15	0.08	1.30	Casella Waste Systems Inc	0.08	1.31	Atmos Energy Corp	0.07	1.23	Mattson Technology Inc
16	0.08	1.38	Helix Energy Solutions Group Inc	0.08	1.40	Southern Co	0.07	1.30	Dot Hill Systems Corp
17	0.08	1.46	Gibraltar Industries Inc	0.08	1.48	Cincinnati Financial Corp	0.07	1.38	Amkor Technology Inc
18	0.08	1.53	SM Energy Co	0.08	1.56	Dominion Energy Inc	0.07	1.45	Anika Therapeutics Inc
19	0.08	1.61	Forward Air Corp	0.08	1.64	XCEL Energy Inc	0.07	1.52	EMC Corp Ma
20	0.08	1.69	Carpenter Technology Corp	0.08	1.73	Avista Corp	0.07	1.59	Empire Resorts Inc
21	0.08	1.77	AK Steel Holding Corp	0.08	1.81	Consolidated Edison Inc	0.07	1.66	Englobal Corp
22	0.08	1.84	Tetra Technologies Inc	0.08	1.89	DTE Energy Co	0.07	1.73	Oracle Corp
23	0.08	1.92	PHI Inc	0.08	1.97	Duke Energy Corp New	0.07	1.80	Cincinnati Bell Inc New
24	0.08	2.00	Unit Corp	0.08	2.05	Exxon Mobil Corp	0.07	1.87	Illumina Inc
25	0.08	2.07	Unifi Inc	0.08	2.14	Entergy Corp New	0.07	1.94	1 800 Flowers Com Inc
26	0.08	2.15	Energen Corp	0.08	2.22	Kelly Services Inc	0.07	2.01	Regeneron Pharmaceuticals Inc
27	0.08	2.22	Schnitzer Steel Industries Inc	0.08	2.30	Vectren Corp	0.07	2.08	Myriad Genetics Inc
28	0.08	2.30	Eog Resources Inc	0.08	2.38	Eversource Energy	0.07	2.15	CVD Equipment Corp
29	0.08	2.37	Hardinge Inc	0.08	2.46	American Financial Group Inc New	0.07	2.22	Lam Resh Corp

Table 14: Top holdings of the equal-weighted climate risk beta sorted regulatory climate risk (brown), physical climate risk and sustainability (green) portfolios. The weights are averages in %, calculated over the period Jan. 2002 to Dec. 2020.

C Selective Climate Risk Beta Sorted Portfolios

We perform the same steps as described in Section 4.4.1 with the only difference that we now exclude all beta estimates with low statistical significance (t-value < 1). Table 15 highlights the top holdings of the value-weighted portfolios. It can be observed that firms like Apple and Meta are not present in the "Brown" portfolio anymore, as it was the case in Table 8. This also affects the cumulative portfolio returns shown in Figure 15. In particular, the "Brown" portfolio moves more or less sideways in the second half of the period, widening the gap between the "Green" and "Brown" portfolios.

	Regulatory Climate Risk (Brown) Portfolio			Physical Climate Risk Portfolio			Sustainability (Green) Portfolio		
	Weight (%)		Company Name	Weight (%)		Company Name	Weight (%)		Company Name
0	4.22	4.22	Exxon Mobil Corp	4.66	4.66	Exxon Mobil Corp	7.91	7.91	Intel Corp
1	2.08	6.30	Conocophillips	3.72	8.38	Chevron Corp New	7.33	15.24	Cisco Systems Inc
2	1.88	8.18	Occidental Petroleum Corp	2.59	10.96	Verizon Communications Inc	4.80	20.04	Microsoft Corp
3	1.74	9.92	Chevron Corp New	2.48	13.44	Walmart Inc	3.21	23.24	Apple Inc
4	1.47	11.39	Devon Energy Corp New	1.74	15.18	AT & T Inc	2.79	26.03	Home Depot Inc
5	1.27	12.66	Valero Energy Corp New	1.59	16.78	Coca Cola Co	2.51	28.54	Oracle Corp
6	1.21	13.86	APA Corp	1.40	18.17	Johnson & Johnson	2.40	30.95	Alphabet Inc
7	1.18	15.04	Eog Resources Inc	1.25	19.42	Procter & Gamble Co	2.39	33.33	Dell Inc
8	1.17	16.22	Halliburton Company	1.22	20.64	Nextera Energy Inc	2.03	35.36	Amazon Com Inc
9	1.17	17.38	Freeport Mcmoran Inc	1.19	21.83	Pepsico Inc	1.66	37.03	EMC Corp Ma
10	1.16	18.55	Anadarko Petroleum Corp	1.16	22.99	Southern Co	1.53	38.56	Yahoo Inc
11	1.00	19.54	NOV Inc	1.15	24.14	Duke Energy Corp New	1.47	40.03	Ford Motor Co Del
12	0.92	20.47	Berkshire Hathaway Inc Del	1.10	25.24	Dominion Energy Inc	1.39	41.42	Best Buy Company Inc
13	0.92	21.38	Southern Copper Corp	1.08	26.32	Berkshire Hathaway Inc Del	1.06	42.49	Corning Inc
14	0.88	22.26	Baker Hughes Co	0.98	27.29	Pfizer Inc	0.74	43.22	Johnson & Johnson
15	0.87	23.13	Coca Cola Co	0.94	28.24	Exelon Corp	0.73	43.96	Procter & Gamble Co
16	0.82	23.94	Hess Corp	0.94	29.18	Conocophillips	0.72	44.68	Juniper Networks Inc
17	0.76	24.70	American Airlines Group Inc	0.94	30.11	International Business Machs Cor	0.66	45.33	Nextel Communications Inc
18	0.76	25.46	Newmont Corp	0.86	30.97	Altria Group Inc	0.63	45.96	Las Vegas Sands Corp
19	0.75	26.21	Mosaic Company New	0.82	31.79	United Parcel Service Inc	0.62	46.58	Berkshire Hathaway Inc Del
20	0.75	26.96	Procter & Gamble Co	0.77	32.56	General Electric Co	0.56	47.14	Sun Microsystems Inc
21	0.73	27.69	Marathon Oil Corp	0.76	33.32	Allstate Corp	0.56	47.70	General Electric Co
22	0.71	28.39	Murphy Oil Corp	0.73	34.05	American Electric Power Co Inc	0.54	48.24	Gilead Sciences Inc
23	0.58	28.98	Chesapeake Energy Corp	0.73	34.79	Mcdonalds Corp	0.53	48.76	Pepsico Inc
24	0.58	29.56	Concho Resources Inc	0.73	35.52	Travelers Companies Inc	0.48	49.25	Qualcomm Inc
25	0.57	30.13	Williams Cos	0.65	36.17	Qualcomm Inc	0.47	49.71	Merck & Co Inc New
26	0.57	30.70	Noble Energy Inc	0.64	36.81	Boeing Co	0.46	50.18	Broadcom Corp
27	0.56	31.26	Exelon Corp	0.58	37.39	Caterpillar Inc	0.46	50.64	Lucent Technologies Inc
28	0.56	31.82	Continental Resources Inc	0.58	37.97	Waste Management Inc Del	0.46	51.10	International Business Machs Cor
29	0.54	32.36	Marathon Petroleum Corp	0.53	38.51	Philip Morris International Inc	0.42	51.52	Sandisk Corp

Table 15: Top 30 companies of the value-weighted climate risk beta sorted portfolios. We exclude all firms with beta estimates of low statistical significance (t-value < 1). The weights are averages in %, calculated over the period Jan. 2002 to Dec. 2020.

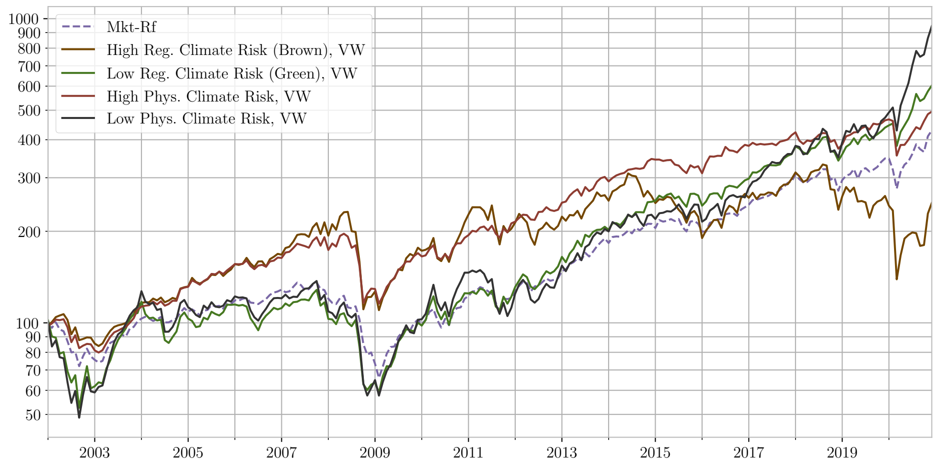

Figure 15: Cumulative returns of the value-weighted climate risk beta sorted portfolio over the period Jan. 2002 to Dec. 2020. We exclude all firms with beta estimates of low statistical significance (t-value < 1) and sort stocks in a high- and low regulatory climate risk portfolio, as well as a high- and low physical climate risk portfolio.

D Climate Risk Beta Distributions

In Figure 16 we plot the cross-sectional distribution of the regulatory climate risk beta (left) and the physical climate risk beta (right) at three points in time: Jan. 2002, Jan. 2012 and Jan. 2020 and observe that the distribution of the physical climate risk beta is strongly skewed to the left in all cases (see Table 16). Also, we observe that only 28.8% of firms have a positive regulatory climate risk beta in 2020.

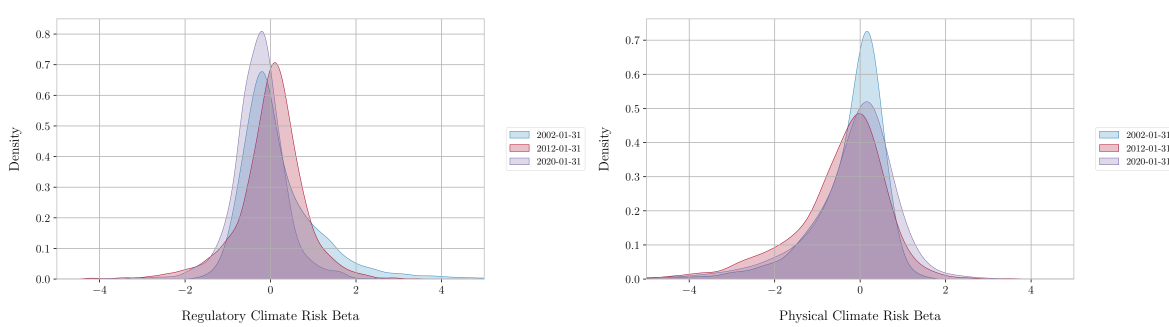

Figure 16: Distribution of the regulatory climate risk beta (left) and the physical climate risk beta (right) at three points in time: Jan. 2002, Jan. 2012 and Jan. 2020.

	Median	Mean	Std. dev.	Skewness	Kurtosis	% Pos
Reg. Climate Risk Beta						
2002-01-31	-0.039	0.216	0.990	2.253	9.732	0.470
2012-01-31	0.073	0.012	0.853	-2.391	38.762	0.555
2020-01-31	-0.254	-0.268	0.684	-0.365	26.695	0.288
Phys. Climate Risk Beta						
2002-01-31	-0.011	-0.264	0.964	-2.751	16.202	0.492
2012-01-31	-0.259	-0.493	1.234	-2.095	14.222	0.371
2020-01-31	0.004	-0.225	1.544	-18.932	735.129	0.502

Table 16: Descriptive statistics of the distributions shown in Figure 16.

In Figure 17 we plot the distribution of regulatory climate risk betas across different industries. We show the distribution for the industries *Electric, Gas, And Sanitary Services*, *Oil And Gas Extraction*, *Petroleum Refining And Related Industries* and *Business Services*. The climate risk betas of the industry *Business Services* is clearly skewed to the right, i.e., towards green firms while the betas of the industry *Oil And Gas Extraction* is skewed to the left, i.e., brown firms. The overlap between the distributions indicate a strong variation of firm-specific climate risks within industries.

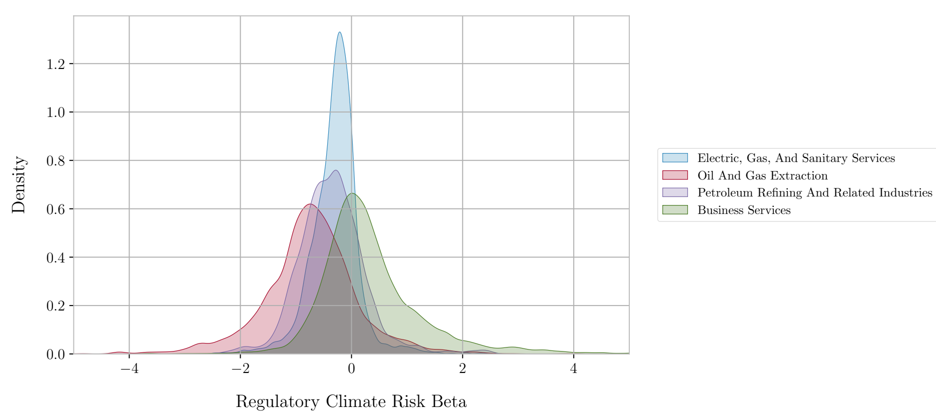

Figure 17: Distribution of the regulatory climate risk betas across different industries.

Figure 18 and 19 visualize the distribution of regulatory climate risk betas within selected industries on an annual basis via boxplots. We observe on average positive betas for firms in the industries *Business Services* and *Communications* and negative betas for firms in the industries *Oil And Gas Extraction* and *Electric, Gas, And Sanitary Services*.

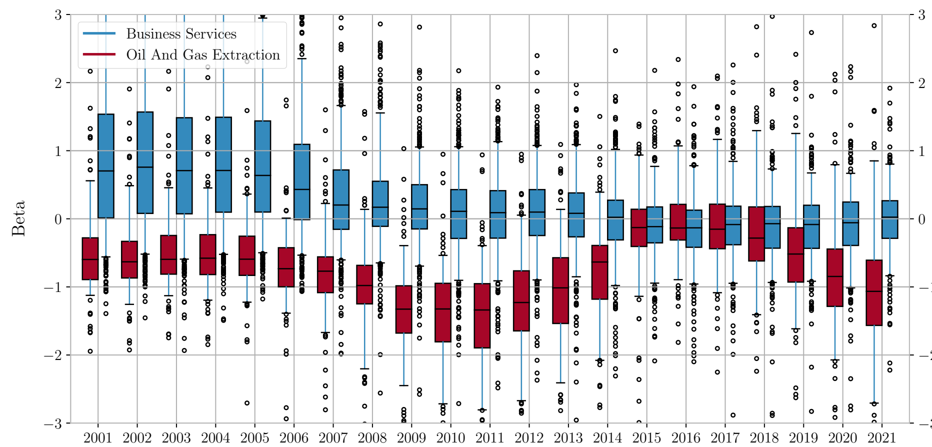

Figure 18: Annual boxplots highlighting the distribution of the regulatory climate risk beta for firms in the industries *Oil And Gas Extraction* and *Business Services*. We resample the monthly betas to an annual frequency by taking the mean.

Figure 19: Annual boxplots highlighting the distribution of the regulatory climate risk beta for firms in the industries *Communications* and *Electric, Gas, And Sanitary Services*. We resample the monthly betas to an annual frequency by taking the mean.

	Model 1a			Model 1b			Model 2			Model 3			Model 4			Model 5			Model 6			Model 7		
Period	Full	1	2	Full	1	2	Full	1	2	Full	1	2	Full	1	2	Full	1	2	Full	1	2	Full	1	2
Const	12.64	10.48	15.03	11.46	8.96	14.24	12.54	10.52	14.79	12.62	10.73	14.72	11.32	8.71	14.23	11.46	8.96	14.24						
	(2.46)	(1.26)	(2.63)	(2.19)	(1.06)	(2.44)	(2.26)	(1.17)	(2.43)	(2.33)	(1.23)	(2.45)	(2.15)	(1.02)	(2.43)	(2.19)	(1.06)	(2.44)						
Beta	-2.91	-0.61	-5.48	-0.86	0.81	-2.73	-2.48	-0.59	-4.58	-1.66	0.21	-3.73	-0.95	0.92	-3.03	-0.64	1.18	-2.67	-0.85	1.05	-2.95	-1.40	0.55	-3.55
	(-2.16)	(-0.29)	(-3.66)	(-0.64)	(0.36)	(-2.02)	(-1.90)	(-0.29)	(-3.15)	(-1.27)	(0.10)	(-2.53)	(-0.73)	(0.43)	(-2.24)	(-0.49)	(0.57)	(-1.95)	(-0.64)	(0.49)	(-2.16)	(-1.25)	(0.32)	(-2.86)
Size	7.01	5.09	9.15	5.83	3.98	7.88	7.61	5.20	10.28	6.50	4.27	8.97	6.88	5.59	8.31	6.21	4.32	8.30	6.83	4.60	9.31	7.08	4.75	9.68
	(5.24)	(2.50)	(5.76)	(3.24)	(1.47)	(3.54)	(4.48)	(2.02)	(5.10)	(3.81)	(1.65)	(4.39)	(3.80)	(2.00)	(3.85)	(3.21)	(1.45)	(3.63)	(3.65)	(1.60)	(4.22)	(4.14)	(1.84)	(4.73)
B2M	-2.17	-2.28	-2.05	-2.30	-0.89	-3.87	-1.94	-1.05	-2.93	-2.06	-1.21	-3.01	-2.43	-1.15	-3.86	-2.28	-1.23	-3.44	-1.51	-0.88	-2.20	-1.30	-0.75	-1.92
	(-1.76)	(-1.18)	(-1.36)	(-1.45)	(-0.37)	(-1.93)	(-1.31)	(-0.44)	(-1.83)	(-1.44)	(-0.55)	(-1.68)	(-1.55)	(-0.47)	(-2.07)	(-1.48)	(-0.54)	(-1.69)	(-1.02)	(-0.39)	(-1.19)	(-0.87)	(-0.32)	(-1.07)
OP	0.54	0.50	0.57	-0.60	-0.89	-0.27	0.26	0.69	-0.23	-0.02	0.02	-0.07	0.21	0.15	0.29	-0.56	-0.90	-0.17	-0.53	-1.01	0.01	-0.73	-1.12	-0.29
	(0.92)	(0.76)	(0.58)	(-0.83)	(-0.94)	(-0.25)	(0.36)	(0.79)	(-0.20)	(-0.03)	(0.02)	(-0.06)	(0.32)	(0.16)	(0.29)	(-0.78)	(-0.94)	(-0.16)	(-0.79)	(-1.08)	(0.01)	(-1.14)	(-1.22)	(-0.33)
INV	0.32	-0.82	1.58	0.37	-0.37	1.19	0.40	-0.72	1.64	0.52	-0.47	1.62	0.30	-0.51	1.20	0.42	-0.23	1.14	0.22	-0.55	1.07	0.49	-0.08	1.11
	(0.54)	(-0.95)	(2.19)	(0.54)	(-0.40)	(1.19)	(0.67)	(-0.87)	(2.09)	(0.78)	(-0.52)	(1.72)	(0.47)	(-0.57)	(1.33)	(0.63)	(-0.25)	(1.15)	(0.34)	(-0.66)	(1.14)	(0.81)	(-0.09)	(1.27)
Sus							0.91	0.57	1.28							-0.05	-1.38	1.44	-0.10	-1.06	0.96	0.20	-0.24	0.69
							(1.58)	(0.64)	(1.84)							(-0.06)	(-1.24)	(1.39)	(-0.15)	(-1.17)	(0.95)	(0.31)	(-0.29)	(0.67)
Reg										-0.15	1.47	-1.96				-0.40	1.54	-2.56	0.28	2.04	-1.66	0.60	1.75	-0.69
										(-0.21)	(1.34)	(-2.59)				(-0.57)	(1.61)	(-2.94)	(0.45)	(2.38)	(-2.08)	(1.04)	(2.34)	(-0.85)
Phys													1.60	2.26	0.88	1.50	2.08	0.85	1.75	2.17	1.27	1.94	2.15	1.70
													(2.14)	(1.91)	(1.02)	(2.37)	(2.23)	(1.04)	(2.73)	(2.34)	(1.47)	(3.38)	(2.67)	(2.08)
Fixed effects	None			None			None			None			None			None			Sector fixed effects			Industry fixed effects		
Months	228	120	108	228	120	108	228	120	108	228	120	108	228	120	108	228	120	108	228	120	108	228	120	108
Observations	810766	810766	810766	189586	189586	189586	449319	449319	449319	331025	331025	331025	241756	241756	241756	189586	189586	189586	189586	189586	189586	189586	189586	189586
Firms	8151	8151	8151	3005	3005	3005	5621	5621	5621	4927	4927	4927	3660	3660	3660	3005	3005	3005	3005	3005	3005	3005	3005	3005
R2 (%)	2.86	3.12	2.57	6.04	6.65	5.37	4.03	4.54	3.46	4.53	4.73	4.32	5.54	6.31	4.67	7.24	8.11	6.26	11.36	12.77	9.79	29.20	32.70	25.32
Adj. R2 (%)	2.71	2.99	2.40	5.43	6.01	4.78	3.72	4.23	3.15	4.10	4.32	3.87	4.95	5.70	4.11	6.26	7.10	5.32	9.41	10.80	7.87	22.63	26.17	18.70

Note: *p<0.1; **p<0.05; ***p<0.01

Table 17: Fama-MacBeth regression performed over the periods Jan. 2002 to Dec. 2020 (Full), and the two subperiods Jan. 2002 to Dec. 2011 (1) and Jan. 2012 to Dec. 2020 (2). Model 1 is comprised of the classic risk factors that enter the Fama-French five-factor model. Models 2 to 4 extend this model by one of the climate factors and Model 5 contains all climate factors. With Model 6 and 7 we control for fixed effects using sector dummies in Model 6 and industry dummies in Model 7. We consider 10 sectors (divisions) and 65 industries (with at least 1000 observations each) according to the SIC scheme. We report the annualized risk premia in percent and heteroskedasticity and autocorrelation (HAC) adjusted t-values (Newey and West (1986) standard errors with three lags). All characteristics except dummy variables are standardized for each of the n cross-sectional regressions. Also we exclude all observations with missing values in the cross sectional regression which causes the number of observations to decline relative to Model 1 as the number of firms with topic exposures is limited.