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Climate Change Concerns and the Performance of Green vs. Brown Stocks

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Abstract. We empirically test the prediction of Pástor et al. (2021) that green firms outperform brown firms when concerns about climate change increase unexpectedly, using data for S&P 500 companies from January 2010 to June 2018. To capture unexpected increases in climate change concerns, we construct a daily Media Climate Change Concerns index using news about climate change published by major U.S. newspapers and newswires. We find that on days with an unexpected increase in climate change concerns, the green firms' stock prices tend to increase, whereas brown firms' prices decrease. Furthermore, using topic modeling, we conclude that this effect holds for concerns about both transition and physical climate change risk. Finally, we decompose returns into cash flow and discount rate news components and find that an unexpected increase in climate change concerns is associated with an increase (decrease) in the discount rate of brown (green) firms.

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1. Introduction

Many consider climate change one of the biggest challenges of our time. However, there is disagreement on the magnitude and the causes of the problem and how to address it. As a result of these differing views, some customers, regulators, and investors have strong preferences for sustainable solutions and investments that tackle the climate change problem, whereas others do not. Moreover, these preferences can change with new information. These preference shifts can affect the prices of financial assets (Fama and French 2007). Anecdotal evidence suggests that preference shifts have caused rapid growth in sustainable (green) investing (GSIA 2018) and a massive fossil fuel (brown) disinvestment campaign (Halcoussis and Lowenberg 2019). These investment trends can be triggered or accentuated, for instance, by international conferences on climate change (e.g., the 2012 United Nations (UN) Climate Change Conference), international agreements (e.g., the Paris agreements), or new regulatory proposals (e.g., the Climate Action Plan).[1]

Pástor et al. (2021) propose a theoretical framework to model the impact of changes in sustainability preferences on asset prices. In the specific case of climate change, their model predicts that green stocks outperform brown stocks *when concerns about climate change strengthen unexpectedly*. The authors posit two mechanisms for this. First, investors can adjust their expectations about future green versus brown firms' cash flows. This change in expectations results from a change in customers' and regulators' preferences for sustainability solutions. Due to an unexpected increase in climate change concerns, lawmakers are more likely to propose and implement legislation that would harm brown firms' cash flows relative to green firms. Customers are more likely to buy sustainable products. Second, their model assumes that agents care about environmental, social, and governance (ESG) criteria and climate change's social impact. Hence, investors with high sustainability preferences derive utility from owning shares in green firms rather than brown ones. Under their model assumptions, Pástor et al. (2021) then show that the higher (respectively, lower) the wealth-weighted mean of ESG tastes of investors, the lower (respectively, higher) the expected excess returns of green (respectively, brown) firms. Thus, an increase in customer and/or investor preferences for green firms, because of unexpected increasing concerns about climate change, has an immediate effect on stock prices. This can be seen in the discounted cash flow pricing model in Pástor et al. (2021) (equation (37)). When faced with unexpected increases in climate change concerns, the customer channel reduces (boosts) the net cash flows of brown (green) firms, whereas the investor channel increases (decreases) the discount rate of brown (green) firms. Both channels then contribute to a decrease (increase) in stock prices of brown (green) firms. This paper empirically tests the prediction of Pástor et al. (2021) that green firms outperform brown firms when concerns about climate change increase unexpectedly.

We test this prediction using daily returns of S&P 500 stocks and a novel proxy for unexpected changes in climate change concerns computed from news articles published on the same day. We use news articles for several reasons. First, as mentioned by Nimark and Pitschner (2019), consumers and investors rely on the media as an information intermediary between them and the state of the world. Through the agenda-setting channel, the media influence the concerns about climate change in terms of attention devoted to the issue. In addition, their framing influences people's attitudes and evaluations regarding climate change. A large number of studies have confirmed the underlying hypothesis that media are a powerful tool for increasing public awareness about environmental issues (Boykoff and Boykoff 2007, Sampei and Aoyagi-Usui 2009, Hale 2010). However, it is crucial to disentangle the expected level of concerns about climate change from the shocks that will drive a change in preferences for products and services provided by green vs. brown firms and the investors' tastes holding such stocks. We use regression models to disentangle the effect of shocks in climate change concerns from other factors driving stock market returns.

When exploring stock price reactions, the transient nature of shocks in climate change concerns requires a *daily* time series of climate change concerns. The choice of a daily horizon strikes a balance between timeliness and feasibility. Short measurement horizons are needed, given the fast reaction of stock markets to news, and diminish practical issues related to potential confounding factors when using lower frequencies such as weekly or monthly horizons. A key contribution of our paper is to propose an algorithm that maps news articles into a daily time series that proxies the latent shocks in climate change concerns. The proposed solution is inspired by the two monthly media-based climate change risk indices introduced in Engle et al. (2020). Their first index captures the *attention* about climate change in the *Wall Street Journal* (WSJ). Their second index relies on the Crimson Hexagon proprietary sentiment measure to capture the *negative attention* about climate change in a large set of news outlets. None of these indices are available daily.

The first step in our algorithm is to collect news from ten major and highly circulated U.S. newspapers, including the *Los Angeles Times*, *New York Times*, *Wall Street Journal*, and *USA Today*, and two major newswires: Associated Press Newswires and Reuters News. We only select the media articles for which the subject categorization indicates that the articles discuss climate change. For those articles, we define a novel "concerns score" measuring and combining the levels of negativity and risk discussed in each article. A topic model analysis and an analysis of concern scores per outlet highlight their heterogeneity in terms of coverage, themes, and level of concerns related to climate change, thus confirming the need to consider a broad corpus like ours when proxying climate change concerns captured by U.S. news media. To account for this heterogeneity in our aggregation, we follow Baker et al. (2016) and normalize each news source separately prior to combining the daily climate change concerns' scores into a daily aggregate Media Climate Change Concerns index (MCCC).[2] Finally, we obtain a proxy of unexpected changes in climate change concerns using the prediction error of an explanatory-variables-augmented autoregressive time series regression model calibrated on the MCCC index, which we refer to as unexpected media climate change concerns (UMC).

In our study, we carefully account for potential endogeneity between the daily UMC and the differential in performance of green and brown stocks. The endogeneity may arise due to a potential feedback loop that an exogenous shock leading to increased concern in climate change affects the pricing of green and brown stocks, amplifying the investors' concerns about the impact of climate change and hence strengthening the market impact. We take several actions to mitigate endogeneity. First, we use a conservative approach in selecting the relevant articles. We only retain articles for which the news provider has tagged the topic as "climate change." In addition, we filter this corpus by removing all news articles mentioning keywords related to the stock market and market performance.[3] Second, we define UMC as the shock component in our MCCC index filtered from potential effects of financial-market, energy-related, and macroeconomic variables. Third, we use several sets of contemporaneous controls in our analyses. Throughout the paper, we abstain from any causal interpretation about the relation between the climate change concerns index and the performance of green versus brown stocks.

Our empirical analysis focuses on S&P 500 firms from January 2010 to June 2018. Testing the Pástor et al. (2021) model for this universe requires defining a proxy for the firm's greenness characteristic driving the preferences of consumers and investors for green versus brown stocks. In our study, we quantify a firm's greenness as the ASSET4/Refinitiv carbon-dioxide-equivalent (CO2-equivalent) greenhouse gas (GHG) emissions data scaled by firms' revenue. Thus, the variable measures a firm's emissions intensity: The number of tonnes of CO_2-equivalent GHG emissions necessary for a firm to generate \$1 million in revenue. We base this choice on recent empirical evidence that the level of greenhouse gas emissions is a driver of returns and can thus be considered as a proxy for the greenness variable relevant to consumers and investors. In particular, Bolton and Kacperczyk (2021) study whether carbon emissions affect the cross-section of the U.S. stock market and find that stocks with higher emissions earn higher returns, consistent with investors demanding compensation for carbon risk.

We first analyze the contemporaneous relation between UMC and the daily return of a green-minus-brown (GMB) portfolio that is long in green firms and short in brown firms. Firms below the 25th percentile of the GHG emissions intensity on a given day are defined as green firms, and firms above the 75th percentile as brown firms. We find a significant positive relation, suggesting that green stocks tend to outperform brown stocks on days for which there is an unexpected increase in climate change concerns. When looking at the green (brown) portfolio returns individually, we find a positive (negative) and significant relation with UMC. This relation is stronger, in absolute terms, for the brown portfolio than for the green portfolio. Hence, when there is an unexpected increase in climate change concerns, investors tend to penalize brown firms more than to reward green firms.

Next, we use firm fixed-effects panel regressions to estimate the exposure of individual firms' stock returns to UMC, conditional on their emissions intensity. Our results align with our previous findings: The lower (higher) the emissions intensity, the more positive (negative) the firm's value changes on days with an unexpected increase in climate change concerns. In related work, Ilhan et al. (2021) show that the industry, to a large extent, explains the variation in GHG emissions intensity. Moreover, Bolton and Kacperczyk (2021) find that institutional investors implement exclusionary screening based on emissions intensity in a few industries. Hence, we test whether the GHG emissions intensity still drives UMC exposure at the industry level. We find that is the case for only a minority of industries. The industry is thus a good predictor for the firm's value change on days with large unexpected increases in climate change concerns. Although disclosure of GHG emissions improves over our sample, at least 30% of the S&P 500 firms do not disclose their GHG emissions. We study whether the returns of the nondisclosing firms are also higher for greener than for browner firms when we impute the missing GHG emissions intensity using their industry average. We find that it is the case indicating that the Pástor et al. (2021) prediction also holds for firms that do not disclose their GHG emissions.

We also contribute to understanding the channels through which concerns about climate change news relate to the stock market. In particular, it seems self-evident that not all news articles about climate change lead to an outperformance of green versus brown stocks. Under the Pástor et al. (2021) model, the price reaction is driven by shocks in climate change concerns that influence expectations about firms' cash flows or shocks that change investor preferences. In the final analysis, we investigate the nature of the shocks and study whether the obtained finding with the aggregate UMC variable differs when analyzing the relations for every climate change theme separately. Our analysis identifies four themes (i.e., clusters of topics) related to climate change, namely (in order of prevalence): (i) Business Impact, (ii) Environmental Impact, (iii) Societal Debate, and (iv) Research. We then use the corresponding topic-probability weights per article to compute an MCCC index per theme and repeat the previous panel regression analysis with each thematic UMC as a covariate. We find that, for each thematic dimension, the sign of the coefficient is consistent with the prediction that, on days with unexpected increase in climate change concerns, green firms tend to have a higher return than brown firms. This relation is highly significant for the transition risk themes Business Impact and Societal Debate. A more granular approach at the level of topics is needed to capture the market-relevant concerns about physical risk. We obtain corroborating findings when doing the analysis using monthly returns. For this frequency, we use the approach by Chen et al. (2013) to decompose the monthly returns into a cash flow and discount rate component. We then find only empirical support for a significant change in the discount rate factor returns component in months with an unexpected increase in climate change concerns.

Our results have practical implications for firm managers. First, we provide them with a tool to monitor the climate change concerns as expressed in media articles. Second, we show that the time variation in the UMC matters as a driver of firm value. In periods of high unexpectedly changes in climate change concerns, we find that green firms outperform brown firms. We mainly find evidence of a discount channel, implying that an increase in UMC manifests itself in an increase (decrease) in the cost of equity of brown (green) firms. Third, as the exposure to the UMC variable is driven by the firm's level of greenhouse gas emissions, the firm can decide to invest in improvements to its climate risk profile to benefit from an increase in investors' tastes for green firms.

By empirically verifying the predictions of Pástor et al. (2021) using our new daily MCCC index, we contribute to a growing body of recent studies that focus on understanding the impact of climate change on financial markets. Giglio et al. (2021) provide an excellent review of the literature. Expanding literature specifically focuses on the relation between climate change shocks and realized stock returns. In particular, Hong et al. (2019) find that stock prices of food companies underreact to climate change risks. Choi et al. (2020) find that in abnormally warm weather, stocks of carbon-intensive firms underperform those of low-emission firms. Bertolotti et al. (2019) analyze the impact of extreme weather events on U.S. electric utilities' stock prices. They find substantial price reactions after a hurricane makes landfall. Ramelli et al. (2021) study firms' stock price reactions and institutional investors' portfolio adjustments following the election of Donald Trump and the nomination of Scott Pruitt as the head of the Environmental Protection Agency, both climate change skeptics. They find that investors rewarded carbon-intensive firms but, surprisingly, also companies demonstrating more responsible climate strategies. A recent comprehensive overview of this strand of the literature is Alekseev et al. (2021).

Our study on the relation between unexpected increases in climate change concerns and realized returns of green versus brown firms also relates to the literature on climate risk premia. The Pástor et al. (2021) model predicts that green stocks have lower expected returns due to investors' preference for green stocks and the ability of green stocks to better hedge climate risk. There is mixed empirical evidence about this prediction. Bolton and Kacperczyk (2021) study whether carbon emissions affect the cross section of the U.S. stock market and find that stocks with higher emissions earn higher returns, consistent with investors demanding compensation for carbon risk. Görgen et al. (2020) develop and study a carbon risk factor using a long-short portfolio based on a carbon emissions-related measure but do not find evidence of a carbon risk premium. Engle et al. (2020) build a climate change risk proxy using *Wall Street Journal* news articles to hedge against climate change risks with the mimicking portfolio approach. Although our study is not about climate risk premia, our results do have implications on how to measure it. During periods characterized by increasing concerns about climate change, green stocks can still outperform brown stocks, despite having lower expected returns. This is confirmed by Pástor et al. (2022), showing that the return spread between environmentally friendly and unfriendly stock disappears on days without climate change-concerns shocks. Hence, it is essential to account for climate change concerns when measuring climate risk premia or expected returns.

This paper is organized as follows. Section 2 presents our climate change concerns measure. Section 3 describes our data. Section 4 presents the empirical results on the performance of green vs. brown stocks. Section 5 examines which dimensions drive the relation between unexpected increases in climate change concerns and green vs. brown stock returns. Finally, Section 6 concludes.

2. News Media and Climate Change Concerns

To empirically study the model of Pástor et al. (2021), we need to measure unexpected changes in climate change concerns. Formally, given aggregate climate change concerns at time t, CC_t, we aim to capture

$$\Delta CC_t - \mathbb{E}[\Delta CC_t | I_{t-1}], \tag{1}$$

where ΔCC_t is the change in climate change concerns at time t and I_{t-1} is the information set available at time $t-1$. The challenge is that CC_t is not directly observable.

A potential proxy for CC_t is Gallup's annual Environment poll. One could derive unexpected changes from this survey, in particular unexpected changes in answer to the question about how worried participants are about global warming or climate change. However, this survey (and others) is conducted very infrequently, limiting the measure's usefulness. Instead, we proxy ΔCC_t on a daily basis using news media data.

In the remainder of this section, we first present arguments on the validity of using news media information to proxy for (unexpected) changes in climate change concerns. Then, we describe our methodology to compute the daily UMC variable.

2.1. How the Media Relates to Agents' Changes in Concerns About Climate Change

Several studies observe that the mass media is a powerful tool for increasing public awareness about environmental issues (Schoenfeld et al. 1979, Slovic 1986, Boykoff and Boykoff 2007, Sampei and Aoyagi-Usui 2009, Hale 2010). Media can influence a population's perceptions in two ways: (i) via the informational content communicated in news articles and (ii) by the level of news coverage or attention on a particular subject. We hypothesize that this information is sufficient to derive a meaningful proxy of changes in climate change concerns.

Theoretical models of mass media communication support this hypothesis. For example, the dependency model of the media's effects by Ball-Rokeach and DeFleur (1976) implies that information transmitted by the media affects individuals' knowledge and perceptions when they have less information from other sources, such as personal experience. Most people do not directly experience climate change, given that the most severe consequences of climate change are predominantly future outcomes. As such, the media communicate the majority of the informational content about climate change to the public. The framing theory of Chong and Druckman (2007) is an alternative approach that supports the use of informational content communicated by the media. It states that the presentation of information (i.e., how news is framed or presented) influences people's attitudes toward a subject. Based on this theory, the level of concern about climate change portrayed in the media should directly affect a population's concerns about climate change.

The media bias model of Gentzkow and Shapiro (2006) provides theoretical support that the level of media coverage can proxy for the level of attention on climate change. This model implies that in a highly competitive media environment, individual media outlets tend to cater to their readership's prior beliefs to increase their reputation and revenue. Therefore, if the media perceives that its readers are more concerned about a subject (e.g., climate change), the level of coverage will increase. Additionally, the agenda-setting theory of McCombs and Shaw (1972) states that a consumer of news learns how much importance to attach to an issue from the amount of information published about a news event. This theory implies a connection between news coverage about climate change and the level of importance people attach to climate change.

2.2. Method for Calculating News Article-Level Concerns

Our goal is to capture unexpected changes in climate change concerns. We define concerns as "the perception of risk and related negative consequences associated with this risk." From this definition, we design a score that measures concerns from the informational content of news articles. We rely on two lexicons: (i) a risk lexicon to determine the level of discussion about (future) risk events and (ii) a sentiment lexicon to assess the increase in (the perception of) risk. These lexicons are retrieved from the LIWC2015 software (Pennebaker et al. 2015). The risk lexicon of this software is also used in Stecula and Merkley (2019) to analyze how the news media shape public opinion about climate change.

With these lexicons, we compute what we refer to as the "concerns score." We assume a media universe of $s = 1, \ldots, S$ news sources. On each day $t = 1, \ldots, T$, source s publishes $n = 1, \ldots, N_{t,s}$ articles discussing climate change. Given the number of risk words $RW_{n,t,s}$, number of positive words $PW_{n,t,s}$, number of negative words $NW_{n,t,s}$, and total number of words $TW_{n,t,s}$ in a news article n published on day t by source s, the article's concerns score is defined as

$$concerns_{n,t,s} = 100 \times \left(\frac{RW_{n,t,s}}{TW_{n,t,s}}\right) \times \left(\frac{NW_{n,t,s} - PW_{n,t,s}}{NW_{n,t,s} + PW_{n,t,s}} + 1\right) \Big/ 2. \tag{2}$$

The first ratio of the product, $\left(\frac{RW_{n,t,s}}{TW_{n,t,s}}\right)$, measures the percentage of risk words in the text. Using the percentage rather than the number of risk words accounts for variability in news articles' lengths. The second ratio, $\left(\frac{NW_{n,t,s} - PW_{n,t,s}}{NW_{n,t,s} + PW_{n,t,s}} + 1\right)/2$, measures the degree of negativity (with zero being the most positive text and one being the most negative), which allows us to differentiate between negative and positive articles. Thus, our article-level concerns score can be interpreted as a weighted textual risk measure, where a higher (lower) weight is attributed when a text is more negative (positive).

2.3. Aggregation

We construct a daily index that captures changes in climate change concerns by aggregating article-level concerns scores. First, we define the daily concerns score for day t and a given source s as the sum of the article-level concerns scores across $N_{t,s}$ articles related to climate change:

$$concerns_{t,s} = \sum_{n=1}^{N_{t,s}} concerns_{n,t,s} = N_{t,s} \times \overline{concerns}_{t,s}. \tag{3}$$

As shown in Equation (3), the sum can be expressed in two parts: (i) $N_{t,s}$ (the number of news articles published about climate change on day t by source s) and (ii) $\overline{concerns}_{t,s}$ (the average concerns score in the news published about climate change on day t by source s). Thus, the index captures both the level of media attention and the (average) level of concerns expressed in news articles on a given day for a given source, two important components as explained in Section 2.1. When no news is published about climate change (i.e., $N_{t,s} = 0$), the concerns score in Equation (3) is zero, which is equivalent to a 100% positive sentiment term in Equation (2). As such, our approach assumes that no news is good news.[4]

Second, to account for heterogeneity between sources, we follow the source-aggregation methodology of Baker et al. (2016). For each source s, we compute the standard deviation of the source-specific index over a time range τ_1 to τ_2 $(1 \leq \tau_1 < \tau_2 \leq T)$:

$$\sigma_s = \sqrt{\frac{\sum_{\tau=\tau_1}^{\tau_2} (concerns_{\tau,s} - \overline{concerns}_s)^2}{\tau_2 - \tau_1}}, \tag{4}$$

where $\overline{concerns}_s$ is the sample mean computed over τ_1 to τ_2. We use the standard deviation to normalize the source-specific index over the $t = 1$ to $t = T$ period:

$$nconcerns_{t,s} = \frac{concerns_{t,s}}{\sigma_s}. \tag{5}$$

The normalization is required to aggregate the per-source indices in the next step properly. For instance, consider a source that typically publishes five articles about climate change daily and a competing source that tends to publish one climate change article per day. At some point, however, that second source may publish five articles about climate change. We posit that if the second source suddenly publishes more about climate change than usual, there is a higher probability that a relevant climate change–related event has occurred. We capture this effect with the by-source normalization. Specifically, we add more weight to the signal available in each source's time-series variation than to differences across sources.

Finally, we compute the MCCC index at day t by applying an increasing concave function $h(\cdot)$ to the average of the normalized source-specific climate change concerns for that day:

$$MCCC_t = h\left(\frac{1}{S}\sum_{s=1}^{S} nconcerns_{t,s}\right). \tag{6}$$

We use an increasing concave mapping function $h(\cdot)$ to capture the fact that increased media attention always increases climate change concerns, but at a decreasing rate: One concerning article about climate change may increase concerns, but 20 concerning articles are unlikely to increase concerns 20 times more. One reason for this nonlinear relationship is the "echo chamber" phenomenon, in which groups tend to read the news that agrees with their views, limiting the reach of alternative information to these groups (Flaxman et al. 2016). Another argument comes from the concept of "opinion inertia," which arises, for instance, from the confirmation bias (Doyle et al. 2016). In this case, individuals have difficulties changing their opinion irrespective of available information. An example of a group with opinion inertia are so-called "global warming skeptics." We set $h(\cdot)$ to the square root function in the rest of the paper.

2.4. Unexpected Changes in the Media Climate Change Concerns Variable

Thus far, we developed a methodology to proxy for changes in climate change concerns, ΔCC_t, using media information. Our aim, however, is to derive *unexpected* changes in climate change concerns. Because the media tends to publish unexpected information, it is reasonable to use $MCCC_t$ as a baseline proxy for unexpected changes in climate change concerns. However, some news might still be expected due to numerous factors, such as preannouncements (e.g., planned international conferences) or the presence of stale news (e.g., republishing an article with only slight modifications to the text). Additionally, some studies suggest that the current state of the economy may also influence public perception about climate change (Scruggs and Benegal 2012). Therefore, to capture the shock component in our MCCC index and filter the potential effects of financial-market, energy-related, and macroeconomic variables, we use an explanatory-variables-augmented autoregressive time series model (ARX) to estimate the expected component of $MCCC_t$. We interpret the prediction error as a proxy for the unexpected changes in climate change concerns (i.e., $\Delta CC_t - \mathbb{E}[\Delta CC_t | I_{t-1}]$). We refer to the prediction error as UMC_t in the remainder of the paper. More details are provided in Section 3.2.

2.5. Comparison with Existing Methodologies

Because of the increasing availability of media news, several media-based time series have been proposed over the past years. According to Gentzkow et al. (2019), the most influential media-based time series in economics is the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016). This index uses counts of articles containing at least one keyword from the categories economy, policy, and uncertainty. The index is a simple average of the normalized count across various newspapers. Such a count-based approach is a prototypical example of a media attention-based index capturing the intensity of news coverage. An alternative design is to compute an average feature across all articles that satisfy a condition. This leads to an economic sentiment (respectively, uncertainty) index in case of averaging the sentiment (respectively, uncertainty) in economic news articles. The proposed MCCC index combines the two approaches into a media-based concern index. The more each article about climate change expresses a negative sentiment and high risk, and the more attention the media attaches to it in terms of the number of articles published, the higher the concern.

Although several media-based economic time series already exist, the construction of media-based time series for understanding the impact of climate change on the financial market is more recent. The pioneering contribution by Engle et al. (2020) proposes two monthly indices capturing climate change risk using news articles. A first approach relies on WSJ news articles and a lexicon called the climate change vocabulary (CCV) derived from authoritative texts about climate change. The method extracts a similarity feature between each news article in the corpus and the CCV. The higher the similarity measure, the more likely an article discusses climate change. This similarity feature is then aggregated monthly to obtain a climate change risk index. Their second approach relies on the natural language proprietary algorithms of Crimson Hexagon to compute news articles' negative sentiments about climate change.

We are the first to propose a daily time series capturing climate change concerns in the media. In Table 1, we

Table 1. Media-Based Time Series for Understanding the Impact of Climate Change on the Financial Markets

	This paper	Engle et al.		Kapfhammer et al.	Faccini et al.		Bessec and Fouquau	Bua et al.
Index aims at capturing	Aggregate and thematic media climate change concerns (MCCC)	Intensity of climate change news	Intensity of negative climate change news	Country-specific climate change transition risks	Attention to natural disaster, global warming, international summits and U.S. climate policy	Intensity of transition risks elicited by the U.S. political debate	Media attention, tonality, and uncertainty about environment issues	Intensity of climate change news about physical risk (PR) and transition risk (TR) of climate change
Corpus of news media sources	Ten newspapers: (i) *New York Times*, (ii) *Washington Post*, (iii) *Los Angeles Times*, (iv) *Wall Street Journal*, (v) *Houston Chronicle*, (vi) *Chicago Tribune*, (vii) *Arizona Republic*, (viii) *USA Today*, (ix) *New York Daily News*, (x) *New York Post*. Two newswires: English articles on: (i) Associated Press Newswires and (ii) Reuters News.	*Wall Street Journal*	Calculation by Crimson Hexagon (CH). Full list not disclosed. The starting corpus has over 1,000 outlets, including *New York Times*, *Washington Post*, *Wall Street Journal*, Reuters, BBC, CNN	Dow Jones corpus (news articles written in English). Includes Wall Street Journal	English articles on Reuters news		Four newspapers: (i) *New York Times*, (ii) *USA Today*, (iii) *Washington Post*, (iv) *Wall Street Journal*	English articles on Reuters news
Articles' selection	Articles tagged as "climate change" by the publisher are retained. Keyword based filters are used to eliminate articles discussing stock market performance.	None	Articles containing "climate change"	None	Article containing "climate change" or "global warming"	Articles with "domestic policy" prevalence larger than 40%	Articles tagged as "Commodity/financial market news" and "Economic news"	Only news with European regional focus
Relevant feature extraction per article	Measures concerns as a combination of attention (based on number of articles), polarity (using negative words dictionary), and uncertainty (using uncertainty dictionary)	Measures attention as cosine similarity between tf-idf of WSJ editions and a "climate change vocabulary"	Measures the share of all news articles that are both about "climate change" and that have been assigned to a "negative sentiment" score	Measures association between "country" and "climate risk" both expressed in a word2vec 100-dimensional space calibrated to the monthly corpus. Eight countries are considered.	Measures attention using topic shares	Measures transition risk by manual scoring of articles	Measures attention based on dictionary environmental dictionary. Extend with tonality and uncertainty using LM dictionary	Same approach as *WSJ* index by Engle et al. (2020) but with one physical and one transition risk vocabulary

Table 1. (Continued)

	This paper	Engle et al.		Kapfhammer et al.	Faccini et al.		Bessec and Fouquau	Bua et al.
Sources' aggregation	Equally weighted of normalized indices per source	N.A.	Pooled	N.A.	N.A.		Pooled	N.A.
Frequency	Daily and monthly	Monthly	Monthly	Monthly	Daily	Monthly	Weekly	Daily
Extraction of shock	Augmented AR model	AR model	AR model	N.A.	N.A.	N.A.	N.A.	AR model
Available for download	Yes	Yes	Yes	No	Yes	Yes	No	No
Correlation with MCCC aggregate index		0.37 for MCCC and 0.44 for UMC	0.23 for MCCC and 0.43 for UMC		Ranges from 0.11 to 0.30 for MCCC and from 0.09 to 0.22 for UMC	−0.40 for MCCC and -0.13 for UMC		

Notes. This table reports the list of media-based indices constructed by scholars to understand the impact of climate change on the financial markets. Column order next to "This paper" is with respect to the first release of the methodology on SSRN.

summarize our approach and compare it with the indices by Engle et al. (2020) and the more recent proposals by Kapfhammer et al. (2020), Faccini et al. (2021), Bessec and Fouquau (2021), and Bua et al. (2022). Following Ardia et al. (2019), we organize the comparison based on the main steps of constructing a media-based time series: (i) choice of corpus and selection of the relevant news articles, (ii) calculation of the relevant features per article, (iii) cross-sectional aggregation, and (iv) time-series aggregation. For each of the time series, we find that there is always at least one crucial step in which the proposed MCCC index stands out in terms of enabling researchers to test the association between market returns and concerns about climate change expressed by the media on the same day.

In the last rows of Table 1, we indicate the correlation of the alternative media-based climate change indices with the MCCC and UMC time series when the alternative is available for download. The correlation is at most 44%, confirming the specificity of each index as described by their unique scope and choices in the index design.

3. Data

Our study relies on climate change news articles published by multiple sources, data on firms' annual greenhouse gas emissions, annual revenue, and daily stock returns.

3.1. Climate Change News Corpus

We retrieve climate change-related news articles from U.S. newspapers and newswires from January 1, 2003, to June 30, 2018. We select high circulation newspapers so that these sources have a reasonable chance of influencing the population's concerns about climate change. The selection is based on 2007 circulation data from Alliance for Audited Media. We consider newspapers with a daily circulation of more than 500,000: (i) *New York Times,* (ii) *Washington Post*, (iii) *Los Angeles Times*, (iv) *Wall Street Journal*, (v) *Houston Chronicle,* (vi) *Chicago Tribune,* (vii) *Arizona Republic,* (viii) *USA Today,* (ix) *New York Daily News,* and (x) *New York Post*. In addition, we consider articles published by major newswires: (i) Associated Press Newswires and (ii) Reuters News.

News articles published by these sources are available in DowJones Factiva, ProQuest, and LexisNexis databases. For DowJones Factiva and ProQuest, we identify climate change-related news articles by picking articles in the "climate change" topic category. For LexisNexis, we use the subject climate change with a relevance score of 85 or more.[5] We filter out short news articles with fewer than 200 words, as lexicon-based methods are typically noisy for short texts. Finally, we exclude news articles discussing the stock market using several keyword-based filters to avoid these articles

Table 2. Sources of Climate Change News

Source	Articles		Concern scores		Themes			
	N	%	Mean	%0	BI	EI	SD	R
Panel A: Newswires								
Associated Press Newswires	10,061	0.07	0.32	12.97	49.58	22.39	16.97	11.06
Reuters News	9,288	0.08	0.37	11.79	62.43	17.46	10.47	9.64
Panel B: Newspapers								
New York Times	3,472	0.25	0.38	3.77	41.21	22.16	26.14	10.49
Washington Post	2,442	0.25	0.35	5.45	44.30	20.16	23.68	11.86
Los Angeles Times	1,530	0.20	0.39	3.59	36.76	24.06	29.66	9.52
Wall Street Journal	1,412	0.26	0.32	6.23	56.50	11.55	21.09	10.86
Houston Chronicle	1,385	0.16	0.33	9.60	51.17	18.84	18.82	11.17
Chicago Tribune	482	0.03	0.35	6.85	31.04	24.21	34.01	10.74
Arizona Republic	382	0.04	0.31	14.40	36.88	25.18	26.11	11.83
USA Today	234	0.08	0.44	6.41	30.63	27.78	26.98	14.60
New York Daily News	122	0.02	0.43	9.02	32.06	17.82	41.76	8.35
New York Post	111	0.02	0.44	9.91	35.88	11.69	44.24	8.18

Notes. This table reports, for each source (Panel A: newswires; Panel B: newspapers), the number and the percentage of articles discussing climate change from January 2003 to June 2018. The table also reports the average concern score and the percentage of time a concern score is zero. The last four columns report the percentage of themes' prevalence obtained with the correlated topic model. BI, business impact; EI, environmental impact; SD, societal debate; R, research.

introducing reverse causality in our analyses. The list of the keywords is presented in the online appendix, Section A.

In Table 2, we report statistics about the number of climate change articles published by the sources in our sample. The source that publishes the most about climate change is the Associated Press Newswires, with 10,061 articles. The *Wall Street Journal* publishes the most relative to its total number of articles (0.26%). The *Chicago Tribune*, *New York Daily News*, and *New York Post* published the least about climate change relative to their total number of articles. In particular, although the *Chicago Tribune* has more total articles about climate change than *USA Today* (482 versus 234), *USA Today* publishes more about climate change in relative terms than the *Chicago Tribune* (0.08% versus 0.03%). Table 2 also reports information regarding the concern scores extracted from the articles published by the various sources. In particular, we see that the average score ranges from 0.31 for the *Arizona Republic* to 0.44 for *USA Today* and the *New York Post*. The percentage of articles with a zero concerns score is also much larger for the *Arizona Republic* and the two newswires than the other outlets. This highlights the discrepancies in news reporting, whereby newswire articles are, on average, less opinionated than newspaper articles. This heterogeneity, both in terms of coverage and concern, underlines that standardization by sources before aggregation is necessary, as each source covers and treats information related to climate change differently.

To get a better overview of climate change topics discussed in our set of articles, we estimate the correlated topic model (CTM) of Lafferty and Blei (2006) on our corpus. The CTM model is an unsupervised generative machine-learning algorithm that infers latent correlated topics among a collection of texts.[6] In particular, each text is a mixture of K topics, and each topic is a mixture of V words. The approach yields (i) a vector of topic prevalence $\theta_{k,n,t,s}$ for each news article where $\sum_{k=1}^{K} \theta_{k,n,t,s} = 1$ with $\theta_{k,n,t,s} \geq 0$, and (ii) a vector of word probabilities $\omega_{v,k}$ for each topic, where $\sum_{v=1}^{V} \omega_{v,k} = 1$ with $\omega_{v,k} \geq 0$. To calibrate the CTM on our news corpus, we proceed as follows. First, we estimate the CTM for the range of $K \in \{10, 20, \ldots, 100\}$ topics and select the optimal number using semantic coherence and exclusivity metrics. Second, we manually label the topics by (i) looking at the 10 most-probable words for each topic and (ii) looking at the content of the articles with the largest topic prevalence. Third, we organize (group) the topics into clusters that constitute more general themes related to climate change for ease of interpretation. We construct the themes based on clustering and network analysis. We refer to the online appendix, Section B, for details regarding the topics' and clusters' construction.

With our corpus, we find that $K = 30$ is the optimal number of topics and that topics can be grouped into four themes. In Table 3, we report for each theme the labeled topics together with their 10 highest-probability keywords. In Table 4, we report the topics' and themes' unconditional prevalence and their average climate change concern score. The unconditional prevalence of a topic is obtained as the average of the topic prevalences across all news articles. For a theme, the unconditional prevalence is the sum of its topics' unconditional prevalences. The average climate change concerns score

Table 3. List of Topics Together with Top Ten Keywords in Terms of Probability

Topic	Top ten keywords in terms of probability
	Theme 1: Business impact
Climate summits	agreement, country, climate change, nation, world, talk, deal, meeting, develop country, summit
Agreements/actions	percent, emission, level, target, greenhouse gas emission, goal, country, government, greenhouse gas, year
Climate legislation/regulations	bill, state, cap, legislation, vote, lawmaker, measure, program, global warming, year
Legal actions	state, administration, rule, regulation, agency, plan, court, decision, law, case
Renewable energy	oil, energy, natural gas, gas, pipeline, fossil fuel, renewable energy, wind, nuclear power, world
Carbon reduction technologies	coal, plant, power plant, electricity, carbon dioxide, technology, power, utility, gas, year
Carbon credits market	market, price, scheme, government, credit, euro, tonne, carbon, year, permit
Carbon tax	cost, tax, carbon, energy, price, policy, fuel, carbon tax, biofuel, economy
Government programs	project, money, fund, program, year, development, government, budget, funding, plan
Corporations/investments	company, business, climate change, investor, group, investment, firm, industry, risk, chief executive
Car industry	car, vehicle, standard, methane, gas, year, fuel, industry, automaker, carbon dioxide
Airline industry	airline, flight, ship, emission, aviation, plane, air, pollution, shipping, aircraft
	Theme 2: Environmental impact
Extreme temperatures	year, record, weather, temperature, winter, day, summer, climate change, heat, global warming
Food shortage/poverty	climate change, people, crop, country, farmer, world, food, woman, agriculture, foundation
Hurricanes/floods	flood, storm, hurricane, climate change, sea level, island, disaster, damage, flooding, risk
Glaciers/ice sheets	ice, glacier, year, scientist, foot, ice sheet, mile, melting, sea ice, satellite
Ecosystems	species, animal, plant, bird, disease, climate change, population, year, habitat, extinction
Forests	tree, forests, forest, fire, land, deforestation, carbon, acre, area, soil
Water/drought	water, state, region, river, rivers, drink, year, lake, area, dam
Tourism	site, town, day, mountain, year, snow, mile, park, foot, people
Arctic wildlife	polar bear, sea ice, bear, seal, ice, habitat, species, wildlife, year, population
Marine wildlife	fish, water, sea, oceans, ocean, scientist, coral, alga, year, reef
Agriculture shifts	food, farm, year, wine, plant, meat, production, farmer, coffee, cow
	Theme 3: Societal debate
Political campaign	climate change, issue, leader, president, campaign, election, party, country, speech, policy
Social events	people, world, time, life, climate change, child, year, student, book, global warming
Controversies	climate change, science, global warming, scientist, climate, issue, question, evidence, research, document
Cities	city, people, building, home, energy, light, resident, community, mayor, group
	Theme 4: Research
Global warming	degree, global warming, warming, world, scientist, year, carbon dioxide, atmosphere, greenhouse gas, century
UN/IPCC Reports	report, climate change, risk, impact, global warming, panel, effect, government, world, study
Scientific Studies	study, research, scientist, researcher, data, atmosphere, researchers, climate, effect, model

Notes. This table lists the 30 topics identified in our corpus together with the ten keywords with highest probability for each topic. Topics are regrouped into four themes. For each theme, the topics are sorted by their unconditional prevalence; see Table 4.

for a topic (or a theme) is computed as a weighted sum of the articles' score, where the weights are the topic (or the theme) unconditional prevalences. In addition, we categorize each topic and theme into one of the three types of climate risk put forward in NGFS (2020), namely (i) physical risk, (ii) transition risk, and (iii) liability risk. Physical risks can be acute if they arise from climate and weather-related events and direct destruction of the environment or chronic if they arise from progressive shifts in climate and weather patterns or gradual loss of ecosystem services. Transition risk results from the process of adjustment toward a lower-carbon economy, arising, for instance, from new regulations, technologies, or social and market sentiment. Finally, liability risk can be considered a subset of either physical or transition risks and results from potential climate change-linked legal liability.

From Table 4, we see that the most prevalent theme is Business Impact (prevalence of 51.13%). The topics forming this theme, such as Renewable Energy and Carbon Tax, can be associated with transition risk. The exception is Legal Actions, which is rather related to liability risk. The second most prevalent theme is Environmental Impact (prevalence of 20.17%), the topics of which, such as Extreme Temperatures and Glaciers/Ice Sheets, are related to acute and chronic physical risk, respectively. The third theme is Societal Debate (prevalence of 18.14%), constituted of four topics among which

Table 4. Topics' Unconditional Prevalence, Climate Change Concerns Score, and Climate Risk

	$\overline{\theta}$	$\overline{CC}$	Climate risk
Theme 1: Business impact	51.13	0.30	Transition
Climate summits	11.02	0.32	Transition
Agreements/actions	6.17	0.28	Transition
Climate legislation/regulations	5.28	0.27	Transition
Legal actions	5.11	0.37	Liability
Renewable energy	3.81	0.29	Transition
Carbon reduction technologies	3.80	0.23	Transition
Carbon credits market	3.43	0.23	Transition
Carbon tax	3.03	0.30	Transition
Government programs	2.95	0.33	Transition
Corporations/investments	2.89	0.33	Transition
Car industry	2.44	0.29	Transition
Airline industry	1.20	0.32	Transition
Theme 2: Environmental impact	20.18	0.45	Physical
Extreme temperatures	3.27	0.34	Physical
Food shortage/poverty	2.51	0.62	Physical
Hurricanes/floods	2.39	0.70	Physical
Glaciers/ice sheets	2.35	0.31	Physical
Ecosystems	1.75	0.42	Physical
Forests	1.63	0.39	Physical
Water/drought	1.55	0.44	Physical
Tourism	1.41	0.36	Physical
Arctic wildlife	1.18	0.58	Physical
Marine wildlife	1.15	0.42	Physical
Agriculture shifts	0.98	0.28	Physical
Theme 3: Societal debate	18.13	0.35	Transition
Political campaign	6.01	0.36	Transition
Social events	4.69	0.35	Transition
Controversies	4.68	0.39	Transition
Cities	2.76	0.28	Transition
Theme 4: Research	10.56	0.40	Physical/transition
Global warming	3.80	0.37	Physical/transition
UN/IPCC reports	3.50	0.53	Physical/transition
Scientific studies	3.26	0.31	Physical/transition

Note. This table reports the 30 topics' unconditional prevalence $\overline{\theta}$, average climate change concerns score $\overline{CC}$, and type of climate risk (physical risk, transition risk, or liability risk) following NGFS (2020).

Political Campaign can be associated with transition risk. The last theme is Research (prevalence of 10.56%), formed by topics related to both physical and transition risks. Indeed, although the topic's subject within that theme is often related to (future) physical risk, it is also often accompanied by policy and business recommendations and implications, which enter the realm of transition risk. For instance, the topic "UN/IPCC" captures the content of UN/IPCC reports, for which the Intergovernmental Panel on Climate Change (IPCC)'s institution goal is to "provide regular assessments of the scientific basis of climate change, its impacts and future risks, and options for adaptation and mitigation" (IPCC 2021, p. 1).

The relation between the topics of discussion in our news corpus is displayed via a correlation network in Figure 1. The plot highlights the correlation of prevalences between the topics (i.e., higher likelihood of topics being discussed together in the same news article). The figure clearly shows two clusters of topics corresponding to Business Impact (left) and Environmental Impact (right). In the middle, linking the two clusters, topics are related to the theme Societal Debate. Finally, in the bottom right, we see the three topics corresponding to the theme Research.

In the last four columns of Table 2, we also report the themes' unconditional prevalence for the sources in our sample. The unconditional prevalence of a topic (theme) is obtained as the average of the topic (theme) prevalence across all news articles within a source. Whereas Research is the least covered theme among all sources, we see heterogeneity for the three other themes. For instance, Business Impact is the major theme in all outlets but the *Chicago Tribune*, *New York Daily News*, and *New York Post*, for which Societal Debate is the most prevalent theme of discussion. We also see that Environmental Impact is the second most prevalent theme in newswires, whereas in newspapers, it is Societal Debate. The news media's discrepancies in the coverage of climate change–related topics emphasize the importance of working with several sources when building a media-based index, the objective of which is to capture climate change concerns.[7]

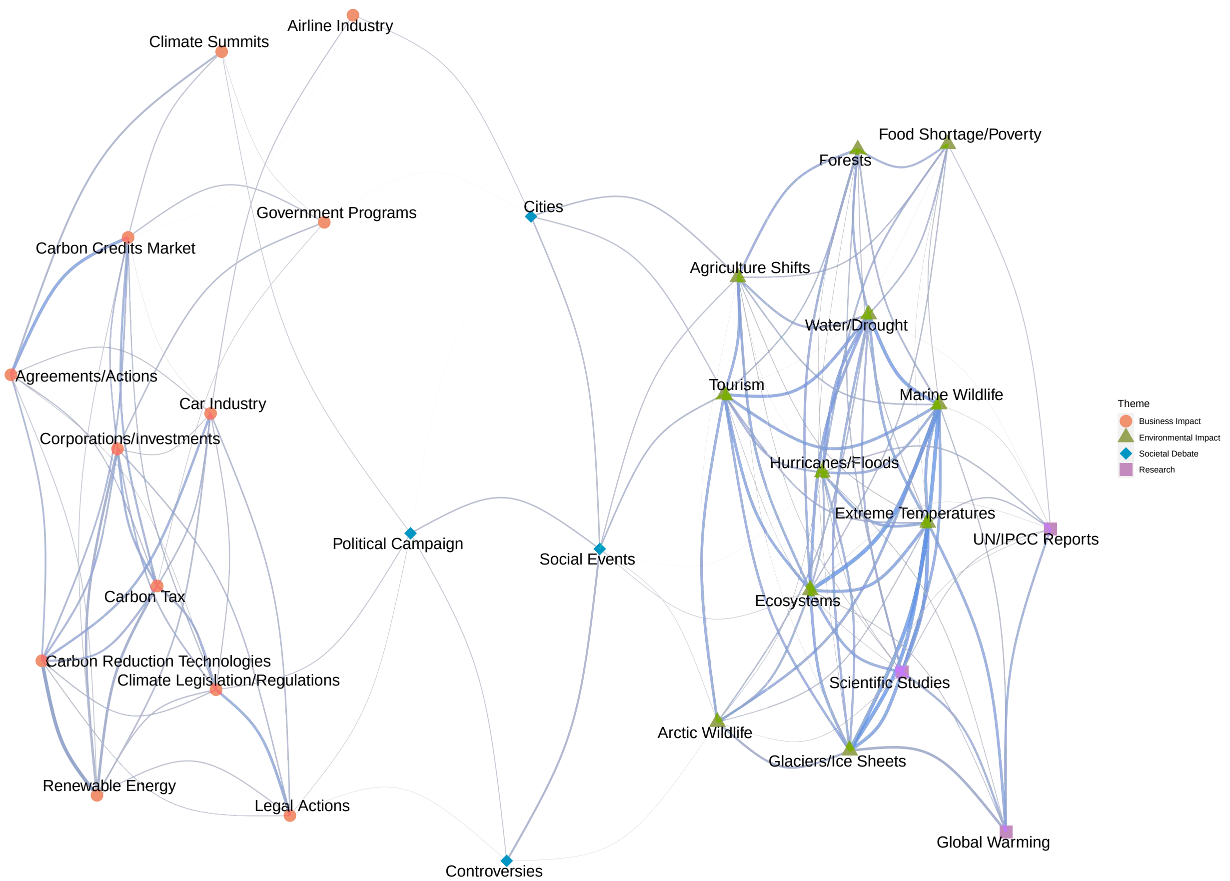
To better understand how much attention the media devotes to these topics over time, we aggregate the topic weights per article into a monthly time series of "article-equivalents" defined as the total of all article weights per topic. This quantity measures the hypothetical number of news articles uniquely discussing a specific topic for a given period. Formally, the number of article equivalents between dates t_1 and t_2 for topic k is defined as $\sum_{t=t_1}^{t_2} \sum_{s=1}^{S} \sum_{n=1}^{N_{t,s}} \theta_{k,n,t,s}$. We then aggregate the number of article equivalents by theme.

In Figure 2, we display the monthly number of article-equivalents for each theme from January 2003 to June 2018. We observe significant time variations in the percentage of coverage devoted to each theme. For instance, Business Impact tends to have a larger number of article-equivalents during months when there are notable conferences on climate change (e.g., 2009 Copenhagen UN climate change conference), and Societal Debate spikes when Trump announced his intention to withdraw from the Paris Agreement.

3.2. MCCC Index

We build the MCCC index following the methodology in Section 2. We compute the source-specific standard deviation σ_s necessary to obtain the standardized source-specific MCCC with media articles from 2003 to 2009. Then, we aggregate the resulting source-specific indices to obtain the MCCC index for 2010 to 2018. In Figure 3, we display the daily evolution of the index from 2003 to 2018. The 2003–2009 period is forward-looking and is not used in the main analysis but is still of interest for validating the index. We interpret the daily index as a proxy for changes in climate change concerns. We also display a

Figure 1. (Color online) Correlation Network of Climate Change Topics



Notes. This figure displays the Spearman correlation network for the 30 climate change topics obtained with the correlated topic model. To keep the network readable, we display only correlations above 0.35. Each topic is assigned to a thematic cluster (Theme 1: Business Impact, Theme 2: Environmental Impact, Theme 3: Societal Debate, and Theme 4: Research).

30-day moving average of the index to help identify trends and events.

First, we see that the index's spikes correspond to climate change events, such as the 2012 Doha UN Climate Change Conference or the Paris Agreement. We also note that climate change concerns, proxied by the moving average, exhibit phases of low and high values. A first period of elevated concerns is observed following the 2007 UN Security Council talks on climate change and lasts until the beginning of 2010, after the Copenhagen UN Climate Change Conference. The second elevated period starts at the end of 2012, near the UN Climate Change conference, and lasts until the Paris Agreement. Later, we note a spike in concerns around the time of U.S. President Donald Trump's announcement that the United States will withdraw from the Paris Agreement. These observations suggest that our index captures meaningful events that correlate with increases in climate change concerns.

We extract the unexpected component of the MCCC index as the prediction error of an explanatory-variables-augmented first-order autoregressive model (i.e., ARX) for the MCCC. Specifically, we consider the following model:

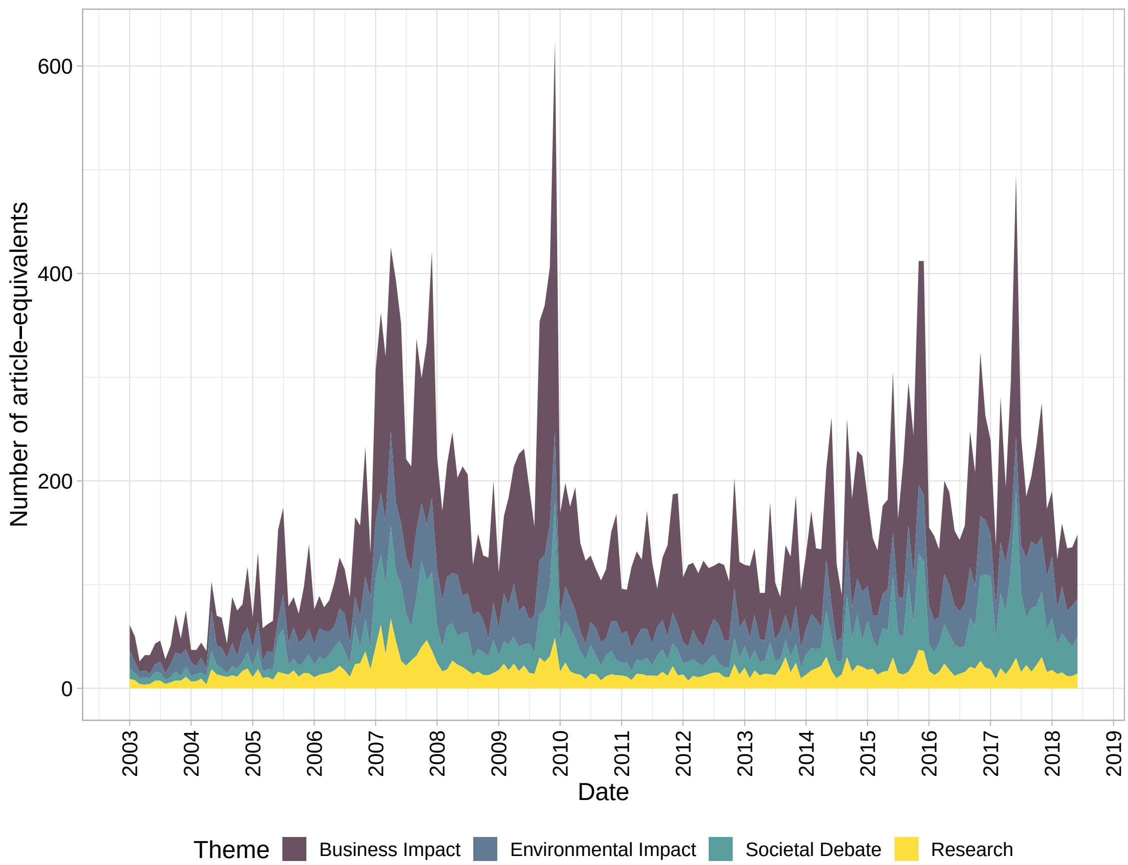
$$MCCC_t = \mu + \rho MCCC_{t-1} + \boldsymbol{\gamma}'\mathbf{x}_{t-1} + \epsilon_t, \qquad (7)$$

where the vector of explanatory variables $\mathbf{x}_t$ is included to mitigate the problem of endogeneity by capturing potential confounders that may affect the MCCC index. The vector includes financial-market, energy-related, and macroeconomic variables, but also variables capturing green/brown performance. We refer to the online appendix, Section C, for the list and description of the variables. We estimate ARX Model (7) on a daily rolling-window basis (of size 1,000) and use the prediction error for UMC_t. Estimation results are available in the online appendix, Section D.

3.3. S&P 500 Stock Universe and Its GHG Emissions Intensity

Our analyses require the identification of green and brown firms. We define green (brown) firms as firms that create economic value while minimizing (not minimizing) damages that contribute to climate change. We

Figure 2. (Color online) Number of Article-Equivalents by Climate Change Theme



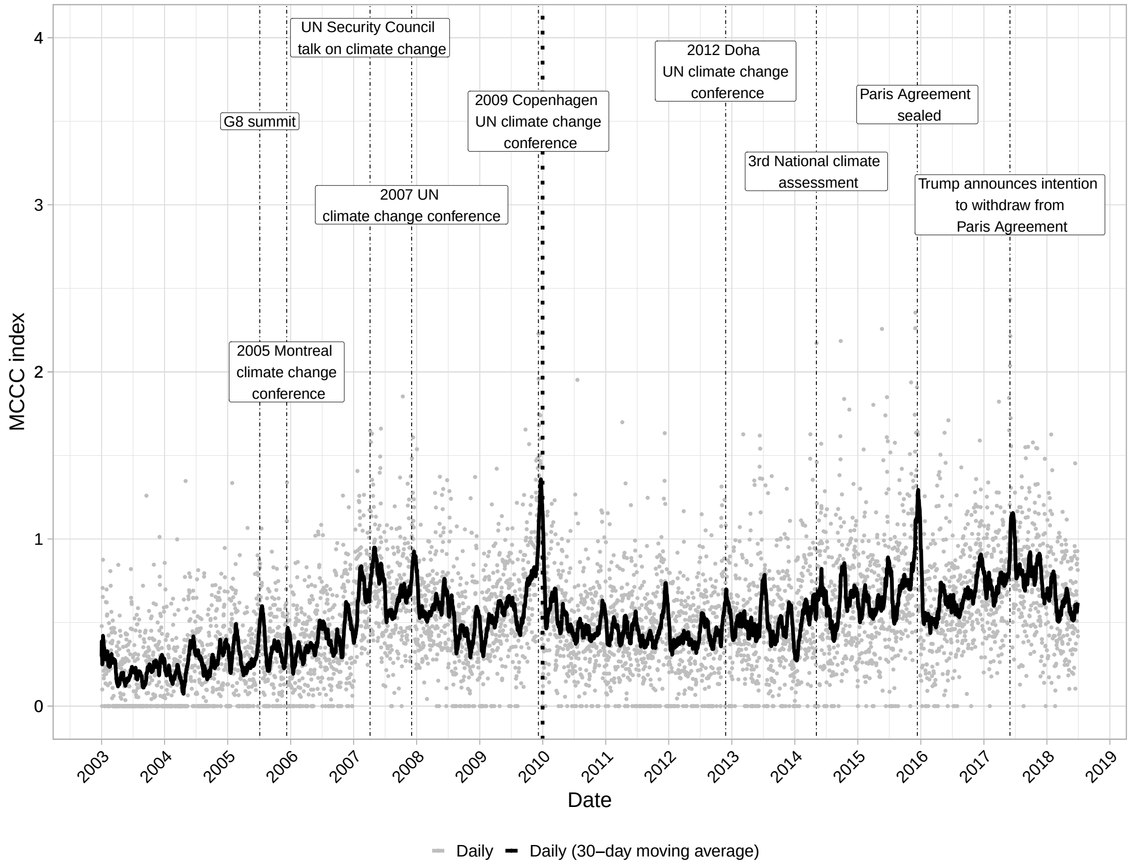
Note. This figure displays the monthly number of article-equivalent publications for each theme from January 2010 to June 2018.

use the GHG emissions disclosed by firms to quantify these damages. We retrieve these variables from the Asset4/Refinitiv database. Similar to Ilhan et al. (2021), we focus on S&P 500 firms because surveys of greenhouse gas emissions typically target these firms.

The GHG emissions variable is separated into three scopes defined by the GHG Protocol Corporate Standard. Scope 1 emissions are direct emissions from owned or controlled sources. Scope 2 emissions are indirect emissions from the generation of purchased energy. Scope 3 emissions are all indirect emissions (not included in Scope 2) that occur in a firm's value chain. These are reported in tonnes of carbon dioxide (CO_2) equivalents. We focus on total GHG emissions, defined as the sum of the three emissions scopes.[8] To account for the economic value resulting from a firm's GHG emissions, we scale total GHG emissions by the firm's annual revenue obtained from Compustat. Whether a firm is classified as green or brown depends on its position within the distribution of firms by their total tonnes of CO_2-equivalent GHG emissions attributed to $1 million of revenue at a point in time. This scaled-GHG variable is referred to as GHG emissions intensity (Drempetic et al. 2020, Ilhan et al. 2021).[9]

In Table 5, we report the percentage of firms in the S&P 500 with available GHG emissions. Although our GHG emissions source differs from Ilhan et al. (2021), who use the Carbon Disclosure Project database, we see that its coverage of S&P 500 firms is similar, with a yearly average at 63.75%. In Table 6, we report the average and standard deviation of GHG intensities for the industries in our sample, as defined by the 48-industries classification in Fama and French (1997).[10] We can notice the considerable heterogeneity across the industries. Whereas the average emissions intensity is 488.75 tonnes of CO_2-equivalent emissions per $1 million in revenue, the 25th and 75th percentiles are 49.92 and 600.28, respectively. The most polluting industry is Utilities, with an average of 4,072 tonnes, and the least polluting industry is Construction, with 4.45 tonnes. The table also displays the percentage of GHG emissions' disclosure per industry, defined as the number of years and firms' pairs with GHG emission data divided by the total number of years and firms' pairs in the industry. We see some heterogeneity across industries, but the disclosure rate is relatively high, especially for the most polluting firms. The across-industry average disclosure is about 65%, and the 25th and 75th percentiles are about 50% and 83%, respectively.

Figure 3. Media Climate Change Concerns Index



Notes. This figure displays the daily MCCC index (gray points) together with its 30-day moving average (bold line) from January 2003 to June 2018. We also report several major events related to climate change (in boxes). The observations before January 1, 2010 (i.e., at the left of the black dotted line) are considered forward-looking, because the data from that period is used to compute the source-specific standard deviation estimate required to normalize the source-specific indices before aggregation into the MCCC index. The observations from January 1, 2010, to the end of the time series (i.e., at the right of the black dotted line) are not forward-looking and correspond to the period for our main analysis.

Finally, we report in Table 6 the percentage of institutional ownership retrieved from Thomson-Reuters Institutional Holdings for the firms that disclose or do not disclose their emissions. The average institutional ownership is high, at around 80% for the two groups. Also, the percentages are high and very similar between the two groups for each industry. Given the high institutional ownership, we can say that the typical investor is knowledgeable about the emissions profile of the stocks.

GHG emissions are typically reported with a one-year delay. Similar to Ilhan et al. (2021), we account for this by shifting the GHG emissions intensity variable by 12 months in our analyses.

4. Empirical Results on the Performance of Green vs. Brown Stocks

In this section, we empirically test the prediction of the theoretical model of Pástor et al. (2021) that green firms outperform brown firms when concerns about climate change increase unexpectedly. We first construct portfolios of green and brown stocks and test the prediction

Table 5. Percentage of Firms with Emissions Data

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2009–2017 Mean
%D	56.73	62.17	65.24	68.12	60.98	60.79	62.71	66.17	70.83	63.75

Note. This table reports the percentage of firms in the S&P 500 universe with available greenhouse gas emissions data for each year (%D).

Table 6. Statistics of GHG Intensities and Disclosures and Institutional Ownership

		GHG intensity		GHG disclosure	Inst. ownership	
Industry	*N*	Mean	Standard deviation	%D	D	ND
Utilities	43	4,072.83	2,271.65	80.00	70.54	71.72
Coal	2	3,034.88	3,761.48	83.33	–	–
Other	9	2,142.59	2,347.55	60.00	77.93	85.02
Steel works, etc.	6	1,903.09	1,211.71	24.24	79.41	68.10
Chemicals	14	1,088.50	1,220.14	82.08	81.21	79.74
Petroleum and natural gas	34	1,033.31	1,462.40	69.41	79.65	89.54
Precious metals	1	776.53	306.53	100.00	81.56	–
Nonmetallic and industrial metal mining	4	759.58	712.83	82.14	83.46	96.09
Consumer goods	14	679.94	1,645.07	86.32	78.66	72.41
Shipping containers	3	675.60	456.54	83.33	78.41	–
Automobiles and trucks	6	621.34	1,274.14	86.96	72.34	80.87
Transportation	16	615.70	375.45	77.68	76.61	79.84
Personal services	5	554.01	671.24	42.86	90.98	89.35
Machinery	15	529.70	2,008.38	63.64	79.87	81.45
Meals, restaurants, hotels, motels	8	500.93	753.12	76.92	73.03	74.75
Defense	1	410.60	617.60	100.00	83.98	–
Business supplies	9	380.62	270.31	91.18	77.77	92.12
Textiles	1	343.13	24.14	60.00	80.54	77.12
Beer and liquor	6	335.49	413.82	93.18	75.61	85.54
Candy and soda	5	263.01	244.26	45.16	62.88	56.03
Food products	19	209.12	283.15	79.86	66.82	70.82
Agriculture	1	207.67	37.09	90.00	82.13	73.24
Rubber and plastic products	2	117.29		50.00	87.15	85.60
Computers	16	115.83	176.02	72.64	83.25	85.29
Electronic equipment	32	109.75	163.45	68.58	80.57	88.47
Pharmaceutical products	29	99.97	156.82	77.60	75.78	91.71
Tobacco products	4	88.81	87.21	82.35	62.33	93.15
Wholesale	11	75.62	402.32	44.19	80.65	77.63
Medical equipment	17	73.44	137.29	53.21	84.81	78.29
Communication	21	69.68	62.67	43.90	63.45	83.53
Apparel	8	64.48	117.47	55.56	84.50	71.67
Entertainment	4	60.54	15.48	12.50	78.98	79.13
Retail	46	57.49	90.43	51.24	75.89	85.46
Construction materials	6	52.57	34.24	52.78	83.81	87.22
Business services	55	49.04	135.39	53.55	78.95	86.59
Real estate	2	42.90	40.28	95.00	–	–
Aircraft	9	41.29	43.11	74.14	76.55	84.63
Recreation	3	39.77	40.36	85.71	88.45	95.42
Measuring and control equipment	15	37.38	45.54	63.74	88.28	88.10
Healthcare	8	37.02	5.40	26.00	87.16	93.04
Printing and publishing	5	36.63	15.02	50.00	100.00	67.19
Electrical equipment	7	33.18	14.49	83.33	79.21	81.66
Banking	31	21.91	16.24	56.02	78.87	81.08
Trading	19	10.39	8.87	49.64	73.20	77.26
Insurance	28	5.08	3.94	61.93	79.35	75.12
Construction	7	4.45	2.15	24.59	83.48	84.23
Shipbuilding, railroad equipment	1	–	–	0.00	–	–
Across-industry mean	12.94	488.75	537.4	64.82	79.27	81.59
Across-industry 25th percentile	4	49.92	40.28	50.62	76.38	77.12
Across-industry 75th percentile	16.5	600.28	671.24	82.84	83.47	87.22

Notes. This table reports summary statistics of the greenhouse gas intensities used to establish firms' greenness and brownness for the industries as defined by Fama and French (1997); note that "Fabricated Products" is missing in our sample. For each industry, the table reports the number of companies (N), the average and standard deviation of greenhouse gas intensities, the percentage of firms disclosing their emissions (%D), and the percentage of institutional ownership for firms that disclose (D) or do not disclose (ND) their emissions.

both using a conditional mean analysis (Section 4.1) and multivariate factor analysis (Section 4.2). Our main analysis is in Section 4.3. Using a firm fixed-effect panel regression model, we test whether the firm's daily stock returns are explained by an interaction effect between the firm's GHG emissions intensity and the UMC variable. The testable prediction is that firms with a higher GHG emission intensity are more negatively exposed to unexpected changes in climate change concerns (see Section 4.3.1). We further test whether this prediction still holds when considering variations in GHG emissions intensity within industries rather than across industries. Ilhan et al. (2021) show that the variation in GHG emissions intensity is, to a large extent, explained by the industry. Moreover, Bolton and Kacperczyk (2021) find that institutional investors implement exclusionary screening based on direct emissions intensity in a few industries. Hence, the negative relation between the firm's exposure and GHG emission intensity may be driven by industry effects (see Section 4.3.2). Finally, as a nonnegligible number of firms do not disclose their GHG emissions (Table 5), we test whether nondisclosing firms are also affected by climate change concerns based on their industry and if this effect differs from firms that disclose their emissions. Given the result of Ilhan et al. (2021), we do not expect differences in stock return changes between disclosing and nondisclosing firms (see Section 4.3.3).

4.1. Conditional Mean Analysis

Each day in the sample, we divide stocks into three groups: green, brown, and neutral. Green (brown) stocks are firms with a GHG emissions intensity variable in the lowest (highest) quartile of all firms' values available on that day. Neutral firms are the remainder of firms that disclose GHG emissions data.[11] We then build, for each day, equal-weighted portfolios for these groups. Because of the one-year delay in emissions reporting, we rely on former-year emissions when building the portfolios. As such, our portfolio formation strategy does not suffer from look-ahead bias.[12]

Our first analysis focuses on the average return of the GMB portfolio conditional on the *UMC* variable. In Figure 4, we display the average performance of the GMB portfolio conditional on threshold values for *UMC*, obtained as the percentiles of *UMC* over the 2010–2018 period. We see a positive relation between the average return and *UMC*. In particular, when *UMC* is above its median, we notice strong increases in the GMB portfolio average return as the threshold becomes larger, especially at the extreme. Moreover, the average GMB portfolio return is always higher when the *UMC* is above the threshold than when it is below. These preliminary findings indicate that green firms outperform brown firms when there are unexpected increases in climate change concerns.

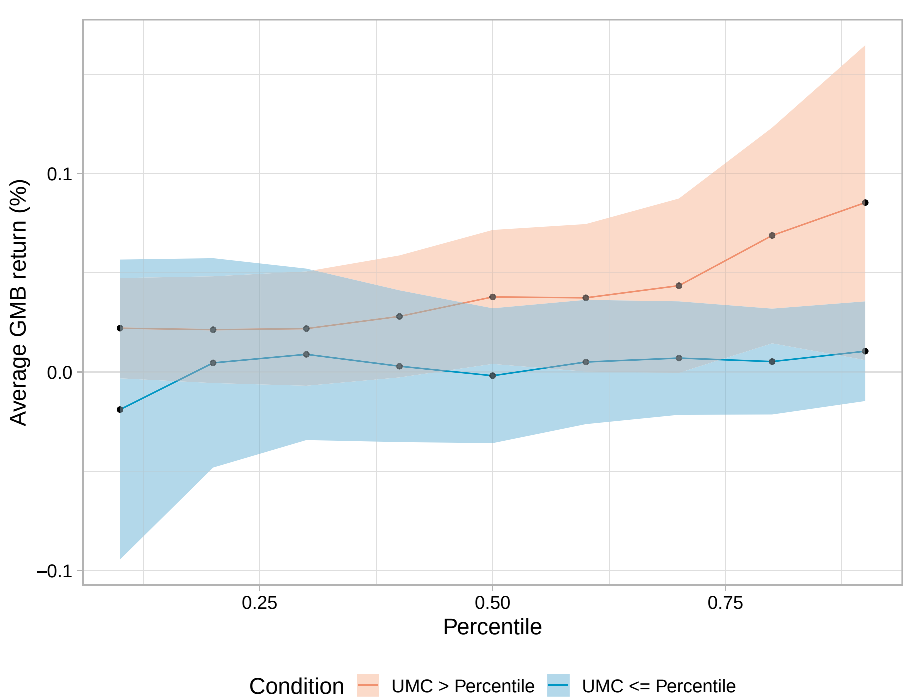
4.2. Multivariate Factor Analysis

We now consider a multivariate linear regression framework to control for other factors that potentially drive stock returns. We regress the green minus brown ($p = GMB$), green ($p = G$), brown ($p = B$), and neutral ($p = N$) portfolios' excess returns, $r_{p,t}$, on UMC_t, and control variables ($\mathbf{CTRL}_t$):

$$r_{p,t} = c_p + \beta_p^{UMC} UMC_t + \boldsymbol{\beta}_p' \mathbf{CTRL}_t + \varepsilon_{p,t}, \tag{8}$$

where c_p is a constant, β_p^{UMC} and $\boldsymbol{\beta}_p$ are regression coefficients, and $\varepsilon_{p,t}$ is an error term. Given the Pástor et al. (2021)

Figure 4. (Color online) Green Minus Brown Portfolio Average Return



Notes. This figure displays the average daily return of the green-minus-brown (GMB) portfolio (vertical axis) conditional on the contemporaneous daily unexpected changes in climate change concerns (*UMC*) being above or below a specific threshold (horizontal axis). Thresholds are set as percentiles of *UMC*. The colored bands report the 95% confidence interval.

model, we expect that $\beta_{GMB}^{UMC} > 0$, $\beta_{G}^{UMC} > 0$, and $\beta_{B}^{UMC} < 0$. We consider four sets of controls in Specification (8):

- **CTRL-1**: *MKT*, the excess market return;
- **CTRL-3**: Set **CTRL-1** augmented with *HML*, the high-minus-low factor, and *SMB*, the small-minus-big factor, of Fama and French (1992);
- **CTRL-6**: Set **CTRL-3** augmented with *RMW*, the robust-minus-weak factor, and *CMA*, the conservative-minus-aggressive factor, of Fama and French (2015), and *MOM*, the momentum factor of Carhart (1997);
- **CTRL-15**: Set **CTRL-6** augmented with *WTI*, the crude oil return, *NG*, the natural gas return, *PROP*, the propane return, *EPU*, the economic policy uncertainty index of Baker, Bloom, and Davis (2016), *VIX*, the CBOE volatility index, the *TED* spread, *TERM*, the term spread factor, and *DFLT*, the default spread factor of Fung and Hsieh (2004), and *FTS*, the flight-to-safety index of Baele et al. (2020).

The variables in **CTRL-1**, **CTRL-3**, and **CTRL-6** are commonly used in the finance literature. The set of controls in **CTRL-15** extends these variables with energy-related and macroeconomic variables to mitigate the potential effect of confounders. We refer to the online appendix, Section C, for more details on the control variables.

Estimation results are reported in Table 7 for the largest set of controls, whereas results for the alternative specifications are available in Table 8. First, we consider the GMB portfolio. We see that the estimated coefficient for *UMC* aligns with our hypothesis. Specifically, a one-unit increase in *UMC* implies an additional daily positive return of 7.2 basis points. This effect is significant at the 5% level. Looking at the green portfolio, we find a positive and significant exposure to *UMC*. We find a negative coefficient for the brown portfolio, significant at the 10% level.

The estimated coefficients for the control variables indicate that the GMB portfolio is positively related to *MKT*, *HML*, *SMB*, *MOM*, and *TERM*, negatively related to *CMA*, *RMW*, *WTI*, and *PROP*. Thus, the GMB portfolio emphasizes small firms with lower growth, aggressive investment policies, and weak operating profits. The *CMA* coefficient (−0.462) is large compared with the other asset-pricing coefficients. This finding is consistent with green firms investing more and brown firms investing less, which is another implication of the Pástor et al. (2021) model. This prediction arises from the idea that green firms' capital costs are lower than brown firms' capital costs. Thus, more investment opportunities for green firms have a positive net present value, resulting in a higher investment level relative to their size than for brown firms. The positive coefficient for *TERM* indicates that green stocks outperform (underperform) brown stocks when there are good (bad) prospects about the economy (as reflected by a positive (negative) term spread). This suggests that investors are more (less) concerned about green investments during good (bad) times when their wealth constraints are less (more) binding, in line with the result of Bansal et al. (2021). The coefficients for *WTI* and *PROP* show that green (brown) firms are negatively (positively) exposed to oil price and natural gas price shocks. We find that the coefficients for the brown portfolio are larger in absolute value than for the green portfolio. The strong positive effect for the brown portfolio is mainly due to the high presence of energy firms in this portfolio.

Table 7. Regression Results of Daily Portfolios' Returns

	GMB	Green	Brown	Neutral
Intercept	0.068*	0.017	−0.051*	0.018
	(0.038)	(0.019)	(0.028)	(0.014)
UMC	0.072**	0.029**	−0.042*	0.006
	(0.031)	(0.014)	(0.023)	(0.01)
MKT	0.127***	1.1***	0.973***	1.036***
	(0.016)	(0.008)	(0.013)	(0.005)
HML	0.112***	0.178***	0.066***	−0.095***
	(0.036)	(0.018)	(0.024)	(0.011)
SMB	0.071***	0.017	−0.055***	0.017**
	(0.026)	(0.011)	(0.02)	(0.008)
CMA	−0.462***	−0.08***	0.382***	0.231***
	(0.048)	(0.028)	(0.035)	(0.016)
RMW	−0.296***	−0.122***	0.174***	0.137***
	(0.04)	(0.019)	(0.031)	(0.013)
MOM	0.078***	−0.088***	−0.165***	−0.075***
	(0.023)	(0.011)	(0.017)	(0.007)
WTI	−8.457***	−2.956***	5.501***	0.125
	(0.695)	(0.336)	(0.51)	(0.221)
NG	−0.362	−0.066	0.296	−0.1
	(0.269)	(0.113)	(0.208)	(0.074)
PROP	−1.254***	−0.405	0.849**	−0.15
	(0.482)	(0.251)	(0.351)	(0.135)
EPU	0.013	−0.005	−0.018	−0.016***
	(0.019)	(0.009)	(0.013)	(0.006)
VIX	−0.003	0.001	0.004**	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
TED	−0.062	−0.059	0.003	−0.06**
	(0.08)	(0.041)	(0.061)	(0.027)
TERM	3.322***	1.12***	−2.202***	0.215*
	(0.366)	(0.164)	(0.273)	(0.111)
DFLT	0.291	0.146	−0.145	0.144*
	(0.211)	(0.103)	(0.159)	(0.082)
FTS	0.079	−0.043	−0.122	−0.002
	(0.125)	(0.057)	(0.097)	(0.053)

Notes. This table reports the results of regressing the daily returns of green-minus-brown (GMB), green, brown, and neutral portfolios on the contemporaneous daily unexpected changes in climate change concerns (*UMC*) and the daily values of the control variables **CTRL-15**; see model (8). The composition of the four portfolios is based on greenhouse gas intensities. Newey and West (1987, 1994) standard errors of the estimators are reported in parentheses. The model is estimated with data from January 2010 to June 2018.

*, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.

In Table 8, we report the estimation results when using alternative sets of controls and alternative percentile thresholds (10–90th and 40–60th percentiles of GHG intensities) for the definition of green and brown

Table 8. Regression Results of Daily Portfolios' Returns: Alternative Controls and Setups

	UMC exposure			
	GMB	Green	Brown	Neutral
	Panel A: 25–75th percentiles			
CTRL-1	0.09**	0.032*	−0.058*	0.004
	(0.038)	(0.017)	(0.03)	(0.012)
CTRL-3	0.085**	0.03*	−0.056*	0.004
	(0.038)	(0.015)	(0.029)	(0.012)
CTRL-6	0.081**	0.031**	−0.05**	0.006
	(0.034)	(0.015)	(0.024)	(0.01)
CTRL-15	0.072**	0.029**	−0.042*	0.006
	(0.031)	(0.014)	(0.023)	(0.01)
	Panel B: 10–90th percentiles			
CTRL-1	0.124**	0.041	−0.083**	0
	(0.057)	(0.027)	(0.041)	(0.012)
CTRL-3	0.113**	0.039	−0.074*	−0.001
	(0.056)	(0.026)	(0.039)	(0.011)
CTRL-6	0.111**	0.04	−0.071*	0.002
	(0.052)	(0.025)	(0.037)	(0.009)
CTRL-15	0.116**	0.041*	−0.075**	0.004
	(0.05)	(0.024)	(0.037)	(0.009)
	Panel C: 40–60th percentiles			
CTRL-1	0.064**	0.025*	−0.039	0.006
	(0.03)	(0.014)	(0.024)	(0.017)
CTRL-3	0.061**	0.023*	−0.038*	0.006
	(0.029)	(0.013)	(0.023)	(0.017)
CTRL-6	0.057**	0.025**	−0.032*	0.007
	(0.028)	(0.012)	(0.019)	(0.015)
CTRL-15	0.05**	0.023*	−0.027	0.006
	(0.025)	(0.012)	(0.018)	(0.015)

Notes. This table reports the results of regressing the daily returns of green-minus-brown (GMB), green, brown, and neutral portfolios on the contemporaneous daily unexpected changes in climate change concerns (*UMC*) for different sets of controls (**CTRL-1**, **CTRL-3**, **CTRL-6**, **CTRL-15**) and green/brown stock classifications (Panel A: 25th to 75th percentiles, Panel B: 10th to 90th percentiles, Panel C: 40th to 60th percentiles of the greenhouse gas emissions intensity). Newey and West (1987, 1994) standard errors of the estimators are reported in parentheses. The model is estimated with data from January 2010 to June 2018.

*, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.

stocks. In all cases, the coefficients for brown firms are always significant and larger (in absolute terms) than the ones of green firms. Hence, the relation between firms' returns and the unexpected changes in climate change concerns seems stronger for brown firms than green firms. This effect can be explained by the observation of Bolton and Kacperczyk (2021) that institutional investors, whose stock ownership in our sample is high (Table 6), implement exclusionary screening based on emissions intensity in a few salient industries. In Section 4.3.2, we look more into details about unexpected changes in climate change concerns in relation to industries.

4.3. Climate Change Concerns in the Cross Section of Stock Returns

The previous section showed that the stock returns of a portfolio of firms with low (high) GHG emissions intensity are positively (negatively) associated with unexpected changes in climate change concerns. We now test whether we can recover this relation using stock-level return exposures to *UMC*. Moreover, we test whether the results still hold when considering variations in GHG emissions intensity within industries rather than across industries. Finally, we also analyze whether firms that do not disclose their GHG emissions are affected by unexpected changes in climate change concerns based on their industry and if this effect differs from firms that disclose their emissions.

4.3.1. Baseline Model. We first define $lGHG_{i,t}$ as the cross-sectionally standardized logarithm of the GHG emissions intensity of firm i available at time t. The standardization is performed by focusing on the cross-sectional variation across firms. We then estimate the following firm fixed-effect panel regression model:

$$r_{i,t} = c_i + \gamma^{lGHG} lGHG_{i,t} + \left(\gamma^{UMC} + \gamma^{UMC}_{lGHG}\, lGHG_{i,t}\right) UMC_t + \boldsymbol{\beta}_i' \mathbf{CTRL}_t + \epsilon_{i,t}, \tag{9}$$

where $r_{i,t}$ is the excess stock return of firm i at time t, and $\mathbf{CTRL}_t$ are control factors. Again, we consider four different sets of controls in the estimation. Coefficients

Table 9. Panel Regression Results of Daily Firms' Returns

	lGHG	*UMC*	*lGHG* × *UMC*
CTRL-1	0.005*	−0.006	−0.027***
	(0.003)	(0.004)	(0.005)
CTRL-3	0.004	−0.008**	−0.024***
	(0.003)	(0.004)	(0.005)
CTRL-6	0.005	−0.005	−0.023***
	(0.003)	(0.004)	(0.005)
CTRL-15	0.006*	−0.001	−0.022***
	(0.003)	(0.004)	(0.005)

Notes. This table reports the estimation results for the firm fixed-effect panel regression of daily stock returns on daily standardized logarithmic greenhouse gas emissions intensity (*lGHG*), daily unexpected changes in climate change concerns (*UMC*), and their interaction (*lGHG* × *UMC*); see model (9). We use four different sets of controls (**CTRL-1**, **CTRL-3**, **CTRL-6**, **CTRL-15**). Standard errors of the estimators are reported in parentheses. The model is estimated with data from January 2010 to June 2018.

*, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.

γ^{lGHG}, γ^{UMC}, and γ^{UMC}_{lGHG} are common to all firms, whereas c_i and $\boldsymbol{\beta}_i$ are firm-specific coefficients.

In Specification (9), the exposure of firms to the unexpected changes in climate change concerns is $(\gamma^{UMC} + \gamma^{UMC}_{lGHG}\, lGHG_{i,t})$, including a common component, capturing the exposure of neutral firms (i.e., firms with log-GHG emissions intensity near the cross-sectional average), and one that depends on a firm's level of log-GHG emissions intensity relative to other firms. We expect a negative value for γ^{UMC}_{lGHG}, so that the higher (lower) a firm's level of GHG emissions intensity, the more negative (positive) the firm's exposure is to unexpected increases in climate change concerns. We also include the firm's log-GHG emissions intensity as a covariate to control for agents' willingness to pay more for greener firms and thus accept lower expected returns. Therefore, we expect a positive coefficient for γ^{lGHG}.

Panel regression results are reported in Table 9. For all sets of controls, we find γ^{UMC}_{lGHG} to be negative and highly significant, consistent with the model predictions. The **CTRL-15** model's coefficients imply that firms with a one standard deviation log-GHG emissions intensity above the cross-sectional mean have negative exposure to unexpected changes in climate change concerns of about −0.023 (i.e., the sum of the coefficients of *UMC* and *lGHG* × *UMC*). We note that the common factor *UMC* is not significant across different sets of controls (**CTRL-3** being the exception). This indicates that the firm with an average level of GHG emissions intensity (i.e., $lGHG = 0$) is not exposed to unexpected changes in climate change concerns. Finally, when we control with the largest set of variables, there is a positive and significant coefficient for *lGHG*, suggesting that brown firms have, on average, higher returns than green firms. This result supports the baseline Pástor et al. (2021) prediction that, in equilibrium, the presence of sustainability preferences leads to a return premium for investments in brown firms.

4.3.2. Industry Analysis. In recent work, Ilhan et al. (2021) show that most of the variation in GHG emissions intensity across firms can be attributed to their industry. Moreover, Bolton and Kacperczyk (2021) find that institutional investors implement exclusionary screening based on direct emissions intensity in a few industries. Hence, the negative relation between the exposure to unexpected changes in climate change concerns and the GHG emissions intensity may be completely explained by industry effects. To test this, we estimate Model (9) for each industry separately.[13] The panel regression estimates are reported in Table 10 using the largest set of controls (i.e., **CTRL-15**). We focus the interpretation on the coefficients for *UMC* (measuring the interindustry effect) and *lGHG* × *UMC* (capturing the intraindustry effect).[14] For the interindustry effect, we expect to find similar results as in the portfolio analysis of Section 4.2. The brownest (greenest) industries will be characterized by a negative (positive) coefficient for *UMC*. If there were no intraindustry effect, we would find a mix of positive and negative exposures of the stock returns within the same sector to the *UMC* factor (being positive for the greenest industries and negative for the brownest industries) and no significant effect of the within-industry variation modeled by the interaction effect between *lGHG* and *UMC*.

We find some confirmation of this in Table 10, where we show the results for the industries ranked from brownest to greenest. We find that for four of the five brownest industries, the coefficient on *UMC* is negative, of which two are significant. The five greenest industries have a positive coefficient, two of them being significant. For most of the other industries, the coefficient is not significant. A few industries deviate from the expected pattern: The most salient cases are Transportation and Automobiles and Trucks. Despite being among the most

Table 10. Panel Regression Results of Daily Firms' Returns: Industries

Industry	*lGHG*	*UMC*	*lGHG* × *UMC*
Utilities	−0.006	−0.076***	0.021
Steel works, etc.	0.091	−0.068	0.194
Chemicals	0.019	−0.035	0.028
Petroleum and natural gas	0.015	−0.044**	0.034
Consumer goods	0.01	0.025	0.013
Automobiles and trucks	0.015	0.115***	0.064
Transportation	−0.05	0.06**	0.043
Machinery	−0.039**	−0.015	−0.066*
Meals, restaurants, hotels, motels	0.009	−0.005	−0.019
Business supplies	0.003	0.029	−0.051*
Beer & liquor	0.029	−0.036	0.016
Food products	−0.003	0.027	−0.002
Electronic equipment	0.024	−0.007	0.011
Computers	−0.005	−0.015	−0.072**
Pharmaceutical products	−0.015	0.018	0.003
Wholesale	0.014	0.04*	−0.04
Medical equipment	0.023	−0.002	−0.011
Communication	−0.056**	0.027	−0.005
Construction materials	0.071**	0.047	−0.254***
Apparel	−0.007	0.025	0.021
Retail	0.022	0.007	0
Business services	−0.011	−0.004	0.005
Aircraft	−0.008	0.013	−0.025
Measuring and control equipment	−0.003	−0.045**	0.027
Healthcare	0.015	−0.102**	−0.232
Electrical equipment	0.008	0.024	0.005
Banking	−0.004	0.039***	−0.002
Trading	0.021	0.035*	0.015
Insurance	0.019	0.021	−0.018
Construction	−0.005	0.052	0.002

Notes. This table reports the estimation results for the fixed-effect panel regression of daily stock returns on daily standardized logarithmic greenhouse gas emissions intensity (*lGHG*), daily unexpected changes in climate change concerns (*UMC*), and their interaction (*lGHG* × *UMC*); see model (9). One panel regression is estimated per industry, and the standardization of lGHG is also done per industry. We rely on Fama and French (1997) for the industry classification and constraint the estimation to industries with more than five firms. The regressions use controls **CTRL-15**. The model is estimated with data from January 2010 to June 2018. Results are sorted by decreasing industries' greenhouse gas emissions intensity.

*, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.

polluting industries, they exhibit a positive and significant exposure to *UMC*. This contradicts the prediction of Pástor et al. (2021) that the brownest firms have a negative price reaction to shocks in climate change concerns. We conjecture that, for these sectors, the firm's GHG is not the relevant firm characteristic driving the climate change taste-related decisions of consumers and investors. In fact, some of the firms in these sectors currently have high GHG intensities but are considered important in the transition toward a low-carbon economy and benefit from government support, notably for transport electrification. This can have a positive price impact through both the consumer and investor channel of Pástor et al. (2021).

Finally, an intraindustry effect (as shown by a significant coefficient for the interaction effect between *lGHG* and *UMC*) is only present for a few industries (i.e., Machinery, Business Supplies, Computers, and Construction Materials). For these industries, we find that the browner the firm, the more the firm tends to lose value on days with an unexpected increase in climate change concerns. Overall, we can conclude that the industry is a good predictor of firms' exposure to unexpected changes in climate change concerns.

4.3.3. Firms That Do Not Disclose GHG Emissions. In our sample, we find that between 28.21% (in 2018) to 44.83% (in 2009) of firms do not disclose their GHG emissions (Table 5). We can expect that, also for nondisclosing firms, greener firms outperform browner firms on days with high shocks in climate change concerns. To test this, we use the industry average GHG emissions intensity as a proxy for the GHG emissions intensity of the nondisclosing firms.[15] For the panel of nondisclosing and disclosing firms, the generalized model becomes

$$\begin{aligned} r_{i,t} &= c_i + \left(\gamma^{lGHG} + \delta^{lGHG}_{UD} UD_{i,t}\right) lGHG_{i,t} \\ &\quad + \left(\gamma^{UMC} + \left(\gamma^{UMC}_{lGHG} + \delta^{UMC}_{lGHG-UD} UD_{i,t}\right) lGHG_{i,t}\right) UMC_t \\ &\quad + \boldsymbol{\beta}_i' \mathbf{CTRL}_t + \epsilon_{i,t}, \end{aligned} \tag{10}$$

where $lGHG_{i,t}$ is defined as the industry average of the logarithmic cross-sectionally normalized GHG emissions intensity for firms that do not disclose (and the actual value for firms that do report). The dummy variable $UD_{i,t}$ is equal to one if the GHG emissions intensity of firm i at time t is not disclosed and zero otherwise. The coefficient of interest is $\delta^{UMC}_{lGHG-UD}$, which measures the difference in exposure coefficients of the interaction term between *lGHG* and *UMC* for the nondisclosing versus disclosing firms.

Estimation results are reported in Table 11 for the different sets of controls. We find that the difference in exposure coefficient is not significantly different from zero between firms reporting their GHG emissions and the nondisclosing ones for which we use the industry average. This result is not surprising given that the effect of unexpected changes in climate change concern on stock returns is mostly driven by the industry. It confirms that the prediction of Pástor et al. (2021) holds for all firms even if they do not disclose their GHG emissions.

5. Dimensions of Climate Change Concerns

Thus far, we established a relation between unexpected changes in climate change concerns and returns of greener versus browner firms. Next, we perform two

Table 11. Panel Regression Results of Daily Firms' Returns: Nondisclosure

	lGHG	*lGHG* × *UD*	*UMC*	*lGHG* × *UMC*	*lGHG* × *UD* × *UMC*
CTRL-1	0.006*	−0.002	−0.008**	−0.027***	0.001
	(0.003)	(0.005)	(0.004)	(0.005)	(0.01)
CTRL-3	0.004	−0.003	−0.011***	−0.024***	−0.001
	(0.003)	(0.005)	(0.004)	(0.005)	(0.01)
CTRL-6	0.005	−0.003	−0.007*	−0.023***	0.001
	(0.003)	(0.005)	(0.004)	(0.005)	(0.009)
CTRL-15	0.005	−0.006	−0.003	−0.022***	0.005
	(0.004)	(0.005)	(0.004)	(0.005)	(0.009)

Notes. This table reports the estimation results for the firm fixed-effect panel regression of daily stock returns on daily standardized logarithmic greenhouse gas emissions intensity (*lGHG*), daily unexpected changes in climate change concerns (*UMC*), their interaction (*lGHG* × *UMC*), and two interactions terms with the undisclosure dummy variable *UD* (*lGHG* × *UD* and *lGHG* × *UD* × *UMC*); see model (9). *UD* takes a value of one when emissions data are not disclosed. The standardized greenhouse gas emissions intensity of firms that do not disclose their greenhouse gas emissions level is set to the average of the firm's industry. We use four different sets of controls (**CTRL-1**, **CTRL-3**, **CTRL-6**, **CTRL-15**). Standard errors of the estimators are reported in parentheses. The model is estimated with data from January 2010 to June 2018.

*, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.

decompositions to obtain a more fine-grained understanding of the channel through which these concerns are related to the changes in the firm's stock prices.

The first decomposition is at the level of the news content captured by the climate change concerns index. The UMC variable aggregates concerns in all news articles about climate change. However, it seems self-evident that not all climate change topics are equally influential in explaining the difference in the performance of greener and browner firms. In particular, we may expect a difference across the four identified themes (Business Impact, Environmental Impact, Societal Debate, and Research) and topics that can be associated with either physical or transition climate change risk. To test this, we use in Section 5.1 the estimated topic model on our corpus of climate change news to construct topical and thematic indices of MCCC and UMC. We then use regression analysis to test for which topical and thematic risk dimensions we still find that, on days with an increase in climate change concerns about that topic or theme, there is a significant differential in stock returns explained by the GHG emissions intensity of the firm.

The second decomposition is at the level of monthly stock returns and aims at testing the implication of the Pástor et al. (2021) model that the effect of climate change concerns can arise from two channels: (i) changes in expected cash flows and (ii) changes in the investor sustainability taste leading to a change in the discount factor. The empirical approach in Section 5.2 proceeds in two steps. First, we combine the price and analysts' earnings forecast data to implement the decomposition of Chen et al. (2013) to attribute the panel of monthly returns into their cash flow and discount rate news component. We then study how the shocks in the monthly topical and thematic climate change concerns relate to each return component.

5.1. Topical and Thematic MCCC and UMC Indices

The topic analysis in Section 3.1 indicates that the corpus of news articles can be summarized using 30 topics split into four themes. These topics differ in terms of prevalence and average level of climate change concerns (Table 4). To track the heterogeneity in climate change concerns across these topics, we construct daily topical MCCC indices. The building block is the daily topic-attribution weighted concern per source s and topic k:

$$concerns_{k,t,s} = \sum_{n=1}^{N_{t,s}} \theta_{k,n,t,s} concerns_{n,t,s}, \tag{11}$$

where $\theta_{k,n,t,s}$ is obtained from the estimated CTM (see Section 3.1). We normalize and aggregate the scores for each index, following the steps of Section 2.3. This yields $K = 30$ topical MCCC indices. Moreover, we also compute four MCCC indices for the aggregate themes by weighting the concern of each article in Equation (11) using the sum of the topic-probability weights of all topics belonging to the respective theme. We then estimate the unexpected changes in climate change concerns for each topic and theme, which we denote by $UMC_{k,t}$, using the procedure outlined in Section 2.4 and Section 3.2.

In Table 12, we report the correlations between the aggregate and the four thematic UMC indices. The unconditional correlations in Panel A range from 0.47 to 0.73. The least correlated themes are Business Impact and Environmental Impact, whereas the most correlated themes are Environmental Impact and Research. Overall conclusions align with the network analysis in Figure 1. In Panel B, we report the correlations in case of large unexpected change in climate change concerns (i.e., when the aggregate UMC is above its 90th percentile). In

Table 12. Correlation Matrix Between Daily Aggregate and Thematic UMC Indices

	BI	EI	SD	R
Panel A: Unconditional correlations				
Aggregate	0.85	0.79	0.82	0.81
BI		0.47	0.66	0.57
EI			0.51	0.73
SD				0.58
Panel B: Correlations when aggregate UMC is high				
Aggregate	0.58	0.41	0.53	0.54
BI		−0.25	0.34	0.04
EI			−0.22	0.37
SD				0.03

Notes. This table reports the pairwise correlations between the daily aggregate and thematic UMC indices. Panel A reports the unconditional correlations, whereas Panel B reports the correlations when daily aggregate UMC is highed than its 90th percentile (*i.e.*, high unexpected changes in climate change concerns). BI, business impact; EI, environmental impact; SD, societal debate; R, research.

this case, the indices are much more distinct than in normal times. We can thus expect that different topics in the climate change discourse relate differently to green and brown firms' returns. In particular, some topics might be more relevant than others regarding the climate change concerns of the different economic agents (e.g., customers, regulators, investors). To test this, we repeat our analysis of Section 4.3.1 with the topical and thematic UMC variables instead of the aggregate UMC variable.

In the left part of Table 13 (column "Daily"), we report the estimation results for the interaction term in Panel Regression (9) using the largest set of controls (i.e., **CTRL-15**) and the various topical and thematic *UMC* indices. It is insightful to analyze the results from the dimension of climate change concerns about physical vs. transition risks. We find that all themes related to transition risk have a negative and significant coefficient for $lGHG \times UMC$. On days with shocks in average concerns about transitioning to a low-carbon economy, we can thus expect that green firms outperform brown stocks. This interpretation holds for all topics within the themes Business Impact, Societal Debate, and Research, except for the topics Car Industry and Scientific Studies. We only find a similar result for physical risk at the level of specific topics within the Environmental Impact theme, namely for Hurricanes/Floods, Glaciers/Ice Sheets, Water/Drought, and Tourism. Understanding the market response around concerns about physical risk thus requires a more fine-grained approach disentangling the market-relevant topics from others.

5.2. Cash Flow and Discount Rate Channels

When concerns about climate change strengthen, the Pástor et al. (2021) model predicts that green firms will gain in popularity among consumers and investors. Through the consumer channel, green firms enjoy an increase in their net cash flows to the detriment of brown firms. As there is also a strengthening of the investor preferences for owning green firms rather than brown firms, the required return for investing in green (brown) firms decreases (increases). This investor channel leads to a reduction in the discount rate of green firms relative to the discount rate of brown firms. An interesting question is how important these two channels are. Additional model assumptions are needed for identification. Chen et al. (2013) propose an approach that requires observing the earnings forecasts revisions, which is not feasible for daily return data. Therefore, we perform the remaining analysis on monthly returns and apply the decomposition of Chen et al. (2013) on firms' monthly capital-gain returns using the implied cost of capital model of Gebhardt et al. (2001).

Formally, denote for firm i at month τ the capital-gain return by $retx_{i,\tau}$. The Chen et al. (2013) decomposition uses analysts' earnings forecasts and firm's accounting data to decompose $retx_{i,\tau}$ into the sum of a cash flow news component, $CF_{i,\tau}$, and discount rate news component, $DR_{i,\tau}$. We refer to the online appendix, Section F, for more details on the decomposition and our implementation. The decomposition requires analysts' earnings forecasts and firm's accounting data that we retrieve from Institutional Brokers' Estimate System (IBES) and Compustat, respectively.[16]

To obtain insight into the relative importance of the cash flow and discount channels on the relation between climate change concerns and stock performance, we use a panel regression that models the stock capital-gain return as a function of an interaction effect between the firm's level of GHG emissions intensity and the shock in concern about climate change of that month. The monthly UMC is obtained by first computing monthly MCCC indices following the same methodology of Section 2, but we aggregate at the monthly frequency. We estimate the unexpected monthly changes in climate change concerns using Equation (7) and a rolling estimation window of 60 months. We estimate Panel Regression (9) using $retx_{i,\tau}$, $DR_{i,\tau}$, and $CF_{i,\tau}$ as the left-sided variable and the various *UMC* indices, namely the aggregate, the thematic, and topical indices. As controls, we use **CTRL-6** alongside the first three principal components of the remaining variables in **CTRL-15** (i.e., excluding the one in **CTRL-6**). These three principal components explain about 66% of the variation of the remaining variables in **CTRL-15**. We use the principal components instead of including the full set of control in **CTRL-15** due to the limited sample size of this monthly analysis compared with our previous daily analysis.

In the right part of Table 13 (columns "Monthly"), we report the interaction term estimates of Panel Regression (9) for monthly returns, cash flow news components, and discount rate components when using the aggregate, the thematic, and the topical UMC variables. First,

Table 13. Interaction Term Estimates: Thematic and Topical UMC Indices

	$lGHG \times UMC_k$			
	Daily return	Monthly return	CF news	DR news
Aggregate *UMC*	−0.022***	−0.445**	0.235	−0.68**
Theme 1: Business impact	−0.028***	−0.271	0.088	−0.36
Climate summits	−0.028***	−0.207	0.07	−0.277*
Agreements/actions	−0.021***	−0.524**	0.051	−0.575**
Climate legislation/regulations	−0.027***	−0.188	0.183	−0.371
Legal actions	−0.013***	0.103	−0.064	0.167
Renewable energy	−0.02***	0.075	0.069	0.007
Carbon reduction technologies	−0.015***	0.33	0.245	0.084
Carbon credits market	−0.019***	−0.524**	−0.1	−0.424*
Carbon tax	−0.014***	−0.633***	−0.216	−0.417
Government programs	−0.019***	−0.219	0.11	−0.329
Corporations/investments	−0.015***	−0.075	−0.034	−0.041
Car industry	−0.001	−0.149	0.05	−0.199
Airline industry	−0.012***	−0.411***	−0.102	−0.309
Theme 2: Environmental impact	−0.006	−0.346	0.151	−0.497*
Extreme temperatures	0.003	0.033	0.097	−0.064
Food shortage/poverty	0.001	−0.319**	0.051	−0.37*
Hurricanes/floods	−0.01***	−0.067	0.108	−0.176
Glaciers/ice sheets	−0.016***	−0.271	−0.17	−0.101
Ecosystems	0.004	−0.407**	−0.121	−0.286
Forests	−0.006	0.112	−0.088	0.2
Water/drought	−0.01**	−0.397**	−0.099	−0.298
Tourism	−0.025***	0.067	0.017	0.051
Arctic wildlife	−0.002	−0.148	−0.009	−0.139
Marine wildlife	0.001	−0.217	0.027	−0.243
Agriculture shifts	0.012**	0.108	−0.003	0.111
Theme 3: Societal debate	−0.023***	−0.369**	0.139	−0.509**
Political campaign	−0.024***	−0.291**	0.127	−0.419***
Social events	−0.01**	−0.403**	0.132	−0.536**
Controversies	−0.022***	−0.269	0.053	−0.321
Cities	−0.014***	−0.028	0.14	−0.168
Theme 4: Research	−0.01**	−0.576**	0.099	−0.676**
Global warming	−0.013**	−0.617***	0.124	−0.741***
UN/IPCC reports	−0.009*	−0.374**	0.049	−0.423*
Scientific studies	−0.002	−0.325	0.029	−0.354

Notes. This table reports the interaction term ($lGHG \times UMC_k$) regression coefficient estimates of firm fixed-effect panel regression (9) on daily stock returns (left column "Daily"), and monthly capital-gain returns, cash flow news components, and discount rate components (right columns "Monthly") when using the aggregate, the thematic, and the topical UMC variables (reported in rows). The daily firm fixed-effect panel regressions use controls **CTRL-15**. To deal with the low number of observations at the monthly frequency, the regressions use controls **CTRL-6** and the first three principal components (explaining 66% of the total variance) of the additional variables in **CTRL-15**. The model is estimated with data from January 2010 to June 2018.
*, **, and ***Significant coefficients at the 10%, 5%, and 1% levels, respectively.

at the aggregate and thematic levels, we see that results for the monthly capital-gain returns are consistent with the results of daily returns in the left part, except for the theme Business Impact.[17] Also, most of the significant terms are negative and related to climate change transition risk at the topics level.

Focusing on the interaction term estimates for the CF and DR news components, we find that the discount rate channel dominates over the cash flow channel in terms of significance. At the aggregate level, the DR news coefficient is negative and significant. At the thematic (topic) level, the DR news coefficient for Environmental Impact (1 topic out of 11), Societal Debate (2 topics out of 4), and Research (2 topics out of 3) are negative and significant. For Business Impact, 3 topics out of 10 are significant and negative for the discount rate channel. Moreover, even accounting for nonsignificant results, the cash flow channel only dominates (in absolute value) in 4 of the 30 topics.

Overall, our results suggest that, for monthly returns, the discount rate channel is the primary channel where the interaction between stock returns, GHG emissions intensity, and unexpected changes in climate change concerns arise. This finding has important consequences for capital budgeting. It implies that green firms enjoy a reduction in the cost of equity in periods of high unexpected climate change concerns and vice versa for brown firms. A caveat of our analysis on the cash flow channel of Pástor et al. (2021) is that the cash flow effects of news are notoriously difficult to observe using monthly returns. Indeed, from the study of Chen et al. (2013), it can be expected that the cash flow effect manifests itself predominantly on longer horizon returns, such as yearly returns or longer. This could be analyzed using distributed lag models, which is beyond the scope of our paper.

6. Conclusion

Our paper empirically verifies the prediction of Pástor et al. (2021) that green firms outperform brown firms when climate change concerns increase unexpectedly.

Our first contribution is to construct a daily proxy that captures unexpected increases in climate change concerns. We do this by collecting news articles published about climate change from major U.S. newspapers and newswires from 2003 to 2018. We design an article-level concerns score and aggregate these scores daily across newspapers to obtain our MCCC index, which proxies for changes in climate change concerns. We show that our index captures several key climate change events that are likely to increase concerns about climate change. Then, we obtain unexpected changes (UMC) as the shock component in our MCCC index filtered from potential effects of financial market, energy-related, and macroeconomic variables. Combining the index construction framework with a topic model, we obtain topical and thematic UMC variables that we associate with climate change transition and physical risk.

Our second contribution is to show that unexpected changes in climate change concerns help explain differences in the performance of green and brown stocks from 2010 to 2018, where greenness is measured by a firm's greenhouse gas emissions intensity. Multiple analyses lead to the same conclusion: All things being equal, green firms outperform brown firms when there are unexpected increases in climate change concerns.

Our third contribution is to shed light on the channels through which stock returns relate to these shocks in climate change concerns. First, we find that, in the cross section of firm returns, the conditional exposure to shocks in climate change concerns is, for most industries, the same for firms belonging to the same industry. Second, we investigate whether the exposure to UMC also holds for firms that do not disclose their greenhouse gas emissions. Using the industry average as a proxy for their emissions, we find it is the case. Third, we use a correlated topic model on our news corpus to investigate which types of climate change concerns relate to the performance of green versus brown stocks. We show that there is significant exposure to almost all topics discussing climate change transition risk, but only a subset of physical risk topics explain the performance of green versus brown firms. Finally, we find that high unexpected changes in climate change concerns increase (decrease) the discount factor of brown (green) firms but do not find evidence of a cash flow effect.

A key message for business leaders is that climate change concerns also matter for their firms' equity values and, importantly, that they can manage their exposure by altering their greenhouse gas emissions intensity. As climate change concerns and investor preferences are time-varying, a monitoring system is recommended. The monitoring of thematic news complements the current widespread practice of monitoring reputation in the media (Fombrun et al. 2015). In this paper, we propose a first design for such a system using U.S. media news.

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Endnotes

[1] These events are reflected in large values for the MCCC index introduced in this paper.

[2] The MCCC index is available at https://sentometrics-research.com/. Examples of recent research using our index are Alekseev et al. (2022), Ballinari and Mahmoud (2021), Campos-Martins and Hendry (2021), and Pástor et al. (2022), among others.

[3] We acknowledge that, although we explicitly exclude news articles discussing the stock market, it may still be that the news published during the calendar day is indirectly influenced by the stock market returns observed during the day. However, given the corpus at our disposal, we believe it is the best we can do.

[4] In their theoretical analysis of carbon prices over the next hundred years, Gerlagh and Liski (2018) assume that individuals' beliefs that climate change will have a long-term impact decrease over time and increase in the presence of information about the damage of climate change. Thus, they make a similar assumption that no news is good news.

[5] LexisNexis indexes each article with metadata information, such as the topic of the article. These metadata tags are associated with a relevance score, where a score of 60 to 84 indicates a minor reference and a score of 85 and above indicates a major reference.

[6] Hansen et al. (2018), Larsen and Thorsrud (2017), Larsen (2021), and Faccini et al. (2021) estimate latent topics using the popular latent Dirichlet allocation (LDA) model of Blei et al. (2003). However, the LDA model does not account for possible correlations between topics. We find that allowing for nonzero correlation with the CTM model generates more coherent topics.

[7] For instance, the attention-based index in Engle et al. (2020) is only based on *Wall Street Journal* articles. In our corpus, this index would correspond mostly to "Business Impact" as the theme's prevalence is 56.50%.

[8] The results from our analysis are similar when excluding Scope 3 emissions.

[9] The environmental dimension of ESG scoring is an alternative variable to classify firms on the green to brown spectrum. However, Drempetic et al. (2020) suggest that these scores do not adequately reflect firms' sustainability. Additionally, Berg et al. (2022) show that the correlations between ESG scores of different data providers are weak, indicating a lack of reliable and consistent scoring methodology across providers.

[10] We use the 48-industries classification of Fama and French (1997) to strike a balance between a sufficient number of firms and homogeneity in terms of GHG intensities within each industry. We consider 47 instead of 48 industries, as the "Fabricated Products" classification is absent in our sample. Industry classification is retrieved from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[11] Our definition of neutral firms does not imply that those firms are carbon neutral (i.e., having net-zero GHG emissions), but rather that they are average in terms of GHG emissions intensity across all firms in our data set.

[12] The GHG emissions are updated yearly but at a different time across firms, and stocks can enter or exit the S&P 500 universe on any day. In the online appendix, Section E, we show that stocks belonging to a given category (green, brown, or neutral) have a high likelihood of remaining in the same category over time. Hence, although the rebalancing is daily, the portfolios' constituents are stable over time.

[13] We only estimate the model for industries with more than five firms. See Table 5 for the number of companies per industry.

[14] For completeness, we also report the estimated coefficient for $lGHG$. Given the high within-industry similarity of the $lGHG$ values, we find that it is insignificant for almost all industries.

[15] As shown in Table 5, the stocks in our sample are mainly held by institutional investors. Hence, we can assume that the typical investor is knowledgeable about the emissions profile of the stocks. As we do not find strong evidence of within-industry effects (see Section 4.3.2), it is reasonable to assume that investors impute the average GHG emissions of the industry to firms that do not disclose them.

[16] We require that a firm has at least 12 valid monthly observations. An observation is discarded when it is an extreme correlation outlier, implemented as $|CF_{i,\tau}| + |DR_{i,\tau}| > 4 \times |retx_{i,\tau}|$, or when the input accounting or IBES data are missing. A manual check shows that excluding the correlation outliers safeguards our analysis against anomalous earnings forecasts leading to unreliable estimates.

[17] For the daily results, the entire cross section of the S&P 500 universe is used because the analysis is not limited by the availability of earnings forecast data.

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