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Abstract

We empirically test the prediction of Pastor, Stambaugh, and Taylor 2020 that green firms can outperform brown firms when climate change concerns strengthen unexpectedly for S&P 500 companies over the period January 2010 - June 2018. To capture unexpected increases in climate change concerns, we construct a Media Climate Change Concern index using climate change-related news published by major U.S. newspapers. We find a negative relationship between the firms' exposure to the Media Climate Change Concerns index and the level of the firm's greenhouse gas emission per unit of revenue. This result implies that when concerns about climate change rise unexpectedly, green firms' stock price increases, while brown firms' stock price decreases. Further, using topic modeling, we analyze which type of climate change news drives this relationship. We identify five themes that have an effect on green vs. brown stock returns. Some of those themes can be related to change in investors' expectations about the future cash-flow of green vs. brown firms, while others cannot. This result implies that the relationship between concern and green vs. brown stock returns arises from both investors updating their expectations about the future cash-flows of green and brown firms and changes in investors' sustainability taste.

Keywords: Asset Pricing, Climate Change, Sustainable Investing, ESG, Greenhouse Gas Emission, Sentometrics, Textual Analysis

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Many consider climate change as one of the biggest challenges of our times. However, there is disagreement on the magnitude of the climate change problem and how to solve it. Conditional on their view on the issue, some people may have high preferences for sustainable solutions and investments tackling the climate change problem, while others may not. Moreover, these preferences can evolve on the arrival of new information. These shifts in preferences can affect the prices of financial assets (Fama and French 2007). Anecdotal evidence of the consequences of sustainability preferences shifts in the financial market over time are the rapid growth of sustainable (green) investing (GSIA 2018) and the 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.*, 2012 UN Climate Change Conference), international agreements (*e.g.*, Paris agreements), or proposals about new regulations (*e.g.*, Climate Action Plan).[1]

Pastor, Stambaugh, and Taylor (2020) propose a theoretical framework outlining the impact that changes in sustainability preferences have on asset prices in the context of climate change. Their model implies that the stock returns of green firms can outperform those of brown firms when concerns about climate change strengthen unexpectedly. The authors posit that this effect arises from two channels: (i) changes in investors' expectations about cash-flows of green versus brown firms and (ii) changes in investors' sustainability tastes. In this paper, we test empirically if unexpected increases in climate change concerns drive green versus brown stocks' performance.

The challenge in testing the above lies in the fact that the concern about climate change over time is latent and must be proxied. We tackle this challenge by deriving unexpected increases in climate change concerns from news articles discussing climate change published in highly circulated U.S. newspapers. Notable examples in using the media to proxy latent variables are Baker, Bloom, and Davis (2016) for the Economic Policy Uncertainty index and Engle, Giglio, Kelly, Lee, and Stroebel (2020) for a monthly

[1] These events are highlighted by large values the Media Climate Change Concern index introduced in this paper.

climate change risk index. To construct our index, we first compute a "concern score" per article that helps segregating concern-expressing news from non-expressing ones. The Media Climate Change Concerns (MCCC) index is then obtained by aggregating the news articles' concern scores every day.

Our empirical study focuses on S&P 500 firms for a period ranging from January 2010 to June 2018. To quantify a firm's greenness, we rely on the ASSET4/Refinitiv CO2 (carbon dioxide) equivalent greenhouse gas (GHG) emissions data scaled by the firms' revenue. Thus, the variable measures the number of tonnes of CO2 equivalent GHG emissions necessary for a firm to generate a one million dollar revenue, namely, the GHG emissions intensity. Firms whose variable is below (above) the 25th (75th) percentile on a given day are defined as green (brown) firms.

We first analyze the contemporaneous relationship between the MCCC index and the daily return of a green minus brown (GMB) portfolio. We find a positive and significant relationship, suggesting that green stocks can outperform brown stocks when 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 relationship with the MCCC index. This relationship is stronger, in absolute terms, for the brown portfolio than for the green portfolio. Thus, in case of an unexpected increase in climate change concerns, investors tend to penalize more harshly brown firms than they reward green firms, on average. This finding is consistent with the behavior of investors using stock screening strategies to filter brown or unsustainable firms from their portfolio and reallocate the capital to other firms, which can be neutral or green (see, *e.g.*, Verheyden, Eccles, and Feiner (2016) and Henke (2016) for analyses on sustainability screening).

For our next analysis, we use panel regressions to estimate the exposure of individual firms' stock returns to unexpected increases in climate change concerns, conditional on the value of the GHG emissions intensity. Our results are in line with our previous findings: The lower (higher) the GHG emissions intensity, the more positive (negative) the exposure to unexpected increases in climate change concern. Consistent with the results of our previous analysis, this implies that green firms outperform brown firms when there is an unexpectedly high increase in climate change concerns. Moreover, we find that stock returns have a positive relationship with the level of GHG emissions intensity. This result suggests that brown firms outperform green firms in the absence of unexpected increases in climate change concern. An additional analysis using the Fama-Macbeth procedure leads to the same conclusions. Overall, our results empirically validate the Pastor, Stambaugh, and Taylor (2020) model.

Finally, a question we are interested in is to whether the effect arises from both channels (cash-flow and taste) as predicted in the model of Pastor, Stambaugh, and Taylor (2020). To answer this question, we split the climate change corpus into topics and derive topical media climate change concern indices. We then evaluate which channel is more likely to be affected for each topic of discussion conditional on their effect on green versus brown firms' stock performances. Our analysis identifies eight themes (*i.e.*, clusters of topics) related to climate change. Five of those themes have a significant relationship with green versus brown firms' stock performance: (i) "Financial and Regulation", (ii) "Agreement and Summit", (iii) "Societal Impact", (iv) "Research", and (v) "Disaster". From those, we posit that the "Financial and Regulation" theme affects the cash-flow channel primarily. On the opposite side, we that the "Research" and "Disaster" themes affect the taste channel. Finally, we that the "Agreement and Summit" theme and the "Societal Impact" theme affect both channels.

By empirically verifying the model's predictions by Pastor, Stambaugh, and Taylor (2020) using our new Media Climate Change Concerns index, we contribute to the literature that focuses on understanding the impact of climate change on financial markets. Thus, we complement several recent studies on the subject. In particular, Hong, Li, and Xu (2019) find that food stock prices are underreacting to climate change risks. Choi, Gao, and Jiang (2020) find that stocks of carbon-intensive firms underperform firms with low carbon emissions in abnormally warm weather. Engle, Giglio, Kelly, Lee, and Stroebel (2020) build a climate change risk proxy using the Wall Street Journal news articles to hedge climate change risk with the mimicking portfolio approach. Ramelli, Wagner, Zeckhauser, and Ziegler (2018) study firms' stock-price reactions and institutional investors' portfolio adjustments at the election of Donald Trump and the nomination of Scott Pruitt as the head of the Environmental Protection Agency, both climate skeptics. Bertolotti, Basu, Akallal, and Deese (2019) analyze the impact of extreme weather events on US electric utilities' stock prices.

1. Hypotheses

In this section, we present the hypotheses tested in our study. The first hypothesis is related to using the news media to proxy for unexpected increases in climate change concerns. The second hypothesis is about the link between climate change concerns and the stock market.

1.1. Media and climate change concern

Several studies have pointed out that mass media are powerful tools for widening public awareness about environmental issues (see, *e.g.*, Schoenfeld, Meier, and Griffin 1979; Slovic 1986; Boykoff and Boykoff 2007; Sampei and Aoyagi-Usui 2009; Hale 2010). Indeed, media can influence the population's perception about a subject in two ways: (i) via the informational content communicated in news articles and (ii) by the level of news coverage or attention towards a particular subject. We hypothesize that this information is sufficient to derive a meaningful proxy of unexpected increases in climate change concerns.

Theoretical models of mass media communication support this hypothesis. For instance, the dependency model of the media effect by Ball-Rokeach and DeFleur (1976) implies that the information transmitted by the media affects individuals' knowledge and perception when they have less information from other sources, such as personal experience. It is reasonable to state that most people do not directly experience climate change, given that the worst 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. Also, the framing theory of Chong and Druckman (2007) is an alternative that supports the use of informational content communicated by the media news. It states that the presentation of information (*i.e.*, how the news is framed or presented) influences the people's attitudes towards a subject. Based on that theory, the level of concern about climate change portrayed in the news media should directly affect the population's concerns about climate change.

Regarding the use of the level of news coverage, the media bias model of Gentzkow and Shapiro (2006) provides theoretical support that the level of coverage can be used to proxy for the level of attention towards climate change. This model implies that in a highly competitive media environment, individual outlets tend to cater to their readership's prior beliefs to increase their reputation and revenue. Therefore, if the media perceive that their readers are more concerned about a subject such as the ones related to climate change, the level of coverage will increase.[2] Alternatively, 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 story. This theory implies a connection between media news coverage about climate change and the level of importance people give to climate change.

1.2. Climate change concerns and stock returns

The theoretical model of Pastor, Stambaugh, and Taylor (2020) predicts that green assets generate negative alpha compared to brown assets, but that green firms can outperform brown firms when concerns about climate change strengthen unexpectedly. Based on this theoretical model, we hypothesize that, on average, when there is a high level of media-based climate change concern, green firms' stock returns are higher than brown firms' stock returns. This relationship arises from two channels: (i) a change in green and brown firms' expected cash-flow and (ii) a change in investor's sustainability taste.

The cash-flow channel arises from investors' expectations regarding changes in regulation and shifts in customers' demands for goods. As climate change concerns rise, there is an increased probability that the lawmakers will take actions that have a negative effect on brown firms' cash-flows relative to green firms' cash-flows. This change

[2] See `https://www.theguardian.com/environment/2019/apr/22/why-is-the-us-news-media-so-bad-at-covering-climate-change`.

in regulation can result in new taxes (*e.g.*, carbon tax), sustainability targets (*e.g.*, US 2015 Clean Power Plan), or subsidies (*e.g.*, Energy Improvement and Extension Act of 2008). Even if regulations are not directly set in place, their expected impact on future cash-flows increases as climate change concerns increase. Also, when there is a sudden increase in climate change concerns, the probability that customers buy green products as opposed to brown products becomes higher (*e.g.*, individuals buy electric cars instead of gasoline cars). Overall, these changes affect firms' future performance: expected cash-flow is reduced for brown firms and increased for green firms.

A complementary channel is related to investors' tastes in assets. A typical assumption in asset pricing is that investors are concerned only with the payoffs from their portfolios. Fama and French (2007) note that violations of this assumption are commonly observed. Thus, in the model of Pastor, Stambaugh, and Taylor (2020), investors can change their tastes with regards to green and brown investments. Specifically, an unexpected increase in climate change concerns will shift the inclination of investors towards green assets positively and towards brown assets negatively. Consequently, investors will be willing to pay more for green firms and less for brown firms, thus, increasing the stock price of green firms and reducing the stock price of brown firms.

2. Media Climate Change Concerns index

We assume a media universe of $s = 1, \ldots, S$ news sources. Each day $t = 1, \ldots, T$, these sources publish $n = 1, \ldots, N_{t,s}$ articles discussing climate change. For each of these articles, we compute a measure of concern based on the textual information. We then aggregate these article-level concern observations at the daily frequency to construct our Media Climate Change Concerns index.

2.1. News article-level concern

Our goal is to capture unexpected increases in climate change concerns. We first define concern as: *The perception of risk and the related negative consequences associated with that risk*. From that definition, we design a score that measures concerns from the informational content of news articles. For that purpose, we rely on two lexicons: A risk lexicon to determine the level of discussion about (future) risk-events and a sentiment lexicon to assess the increase in (the perception of) risk. These lexicons are retrieved from the LIWC2015 software (Pennebaker, Boyd, Jordan, and Blackburn 2015).[3] The risk lexicon of this software has been used in Stecula and Merkley (2019) to analyze how the news media shape the public opinion about climate change.[4]

Using these lexicons, we compute what we refer to as the "concern score." Given the number of risk words $RW_{n,t,s}$, the number of positive words $PW_{n,t,s}$, the number of negative words $NW_{n,t,s}$, and the total number of words $N_{n,t,s}$ in the news article n published at day t by source s, the article's concern score is defined as:

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

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

2.2. Aggregation

Next, we construct an index that captures unexpected increases in climate change concerns by aggregating article-level concern scores into a daily time series. First, we

[3]The academic version is available at `https://liwc.wpengine.com/`.

[4]The media sources used in Stecula and Merkley (2019) are The New York Times, Wall Street Journal, The Washington Post, and The Associated Press, from which the first three overlap with the news sources used in this study.

define the daily concern score at day t for a given source s as the sum of the article-level concern scores across the $N_{t,s}$ climate change-related news articles:

$$concern_{t,s} = \sum_{n=1}^{N_{t,s}} concern_{n,t,s} \,. \tag{2}$$

By taking the sum instead of the average, we capture both the level of concern and attention at a given time and for a given source. As stated in Section 1.1, the attention provided by media to a specific subject is an important signal. Moreover, note that when there is no news released about climate change (*i.e.*, $N_{t,s} = 0$), the concern score in (2) is zero, which is equivalent to a 100% positive sentiment term in (1). Thus, our approach assumes that *no news is good news.*[5]

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

$$\sigma_s = \sqrt{\frac{\sum_{\tau=\tau_1}^{\tau_2} \left(concern_{\tau,s} - \overline{concern}_s\right)^2}{\tau_2 - \tau_1}} \,, \tag{3}$$

where $\overline{concern}_s$ 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:

$$nconcern_{t,s} = \frac{concern_{t,s}}{\sigma_s} \,. \tag{4}$$

The normalization is required to aggregate the per-source indices in the next step properly. For instance, consider the case where a first source publishes five articles about climate change daily while a second source publishes only one news article. At some point in the future, that second source may publish five articles about climate change. If the second source suddenly publishes more about climate change than usual, there is a high

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

probability of a relevant climate change-related event. We capture this with the by-source normalization. Specifically, we add more weight to the signal available in each source's time-series variation than the difference across sources.

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

$$MCCC_t = h\left(\frac{1}{S}\sum_{s=1}^{S} nconcern_{t,s}\right). \tag{5}$$

We use an increasing concave mapping function to capture the fact that increased media attention always increases climate change concerns but at a decreasing rate. Indeed, one concerning article about climate change may increase attention and concerns about climate change. Still, the publication of twenty concerning articles is unlikely to increase attention or concerns twenty times more. One reason for this non-linear relationship is the "echo chamber" phenomenon, which suggests that groups tend to read the news that agrees with their view, limiting the reach of alternative information to those groups (see, *e.g.*, Flaxman, Goel, and Rao 2016). Another argument comes from the concept of "opinion inertia", which arises, for instance, from the confirmation bias (see, *e.g.*, Doyle, Sreenivasan, Szymanski, and Korniss 2016). In this case, individuals have difficulties changing their opinion irrespective of the available information. An example of a group with opinion inertia in climate change is the so-called "global warming skeptics." We set $h(\cdot)$ to the square root function in the rest of the paper.[6]

2.3. Comparison with existing methodologies

Our index construction methodology is related to the approach by Engle, Giglio, Kelly, Lee, and Stroebel (2020). They propose two ways to capture climate risk from the news.

A first approach relies on Wall Street Journal news articles, and a lexicon referred to as the "'Climate Change Vocabulary" derived from authoritative texts on the subject of

[6] We also used $h(x) = \log(1 + x)$ and the results and conclusions were qualitatively similar.

climate change. The method extracts a similarity feature between each news article in the corpus and the Climate Change Vocabulary. The higher the similarity measure, the more likely the article discusses climate change. This similarity feature is then aggregated at the monthly frequency to obtain a climate change risk index. Here, the idea is that media attention towards climate change can proxy the risk level as media will only report on important newsworthy climate change news. In our context, this assumption is valid under the condition that most of the content in those news articles expresses concern. We also consider media attention as a key feature to capture unexpected increases in climate change concerns through the daily aggregation of article-level concern score by taking the sum instead of the average of the scores.

The second method relies on the natural language proprietary algorithms of Crimson Analytics to compute online news articles' negative sentiment about climate change. We also use textual sentiment but extract it with a lexicon approach. We leverage the negative sentiment in the article-level concern score computation using it as a weight for the article-level risk score.

Overall, our index construction combines both the informational content and the level of attention about climate change portrayed in the news media. Moreover, by introducing a textual risk measure in the computation of our article-level concern, we posit that we proxy more accurately unexpected increases in climate change concerns compared to using only a single dimension of the available information (*e.g.*, attention, sentiment, or risk).

3. Data

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

3.1. Climate change news corpus

We retrieve climate change-related news articles from U.S. newspapers for a period ranging from January 1, 2003, to June 30, 2018.[7] We select highly circulated newspapers so that these sources' news articles have a reasonable chance to influence the population's concern about climate change. We choose these newspapers using the 2007 circulation data from the Alliance for Audited Media.[8] We consider high-reaching sources with a daily circulation of more than 500,000 newspapers. According to that condition, the selected newspapers are: (i) The Wall Street Journal, (ii) The New York Times, (iii) The Washington Post, (iv) The Los Angeles Times, (v) The Chicago Tribune, (vi) USA Today, (vii) New York Daily News, and (viii) The New York Post.[9]

News articles published by these sources are available in the DowJones Factiva, the ProQuest, and the LexisNexis databases. For DowJones Factiva and ProQuest, we identify climate change-related news articles by picking news publications within the "Climate Change" topic category. For LexisNexis we identify the relevant news articles using the subject "Climate Change" with a relevance score of 85 or more.[10] We filter out short news articles with less than 200 words as lexicon-based methods are typically noisy on texts of short length.

In Table 1, we report the number of climate change news articles, the total number of news articles, and the percentage of climate change news articles published by the sources in our sample. The source that publishes the most about climate change in terms of the number of publications is the Wall Street Journal, with 3,776 news articles. The New York Times publishes the most relative to its total number of publications, with 0.25%. We note that The Chicago Tribune, the New York Daily News, and the New York Post are the outlets that publish the least relative to their total number of

[7] We use data for the 2003-2009 period to compute the standard deviation parameter required for the index construction and perform our analyses over the 2010-2018 period.

[8] See https://auditedmedia.com/.

[9] Missing among these are the Houston Chronicle and the Arizona Republic, due to their unavailability across the databases used in this study.

[10] 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.

publications compared to the other sources. In particular, while the Chicago Tribune has more publications about climate change than The USA Today (*i.e.*, 509 versus 249), The USA Today publishes more about climate change in relative terms than the Chicago Tribune (*i.e.*, 0.17% versus 0.05%). This heterogeneity highlights that standardization by sources before aggregation is necessary as each newspaper appears to have a different focus regarding content prioritization.

[Insert Table 1 about here.]

For the 20 articles with the highest concern scores in our corpus, we report in Table 2: (i) the publication date, (ii) the concern score, (iii) the level of risk, (iv) the level of negativity, (v) the first 50 characters of the article's title, and (vi) the source. From the title, we see that the most concerning articles appear to be legitimately concerning.[11]

[Insert Table 2 about here.]

To get a better overview of the topic of discussion about climate change, 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.[12] 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 attribution $\theta_{k,n,t,s}$ 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 probability $\omega_{v,k}$ for each topic, where $\sum_{v=1}^{V} \omega_{v,k} = 1$ with $\omega_{v,k} \geq 0$. We estimate the model with $K = 40$ topics; more details are provided in Appendix A.

In Table 4, we report the ten words or collocations (*i.e.*, common sequences of two words) with the highest probability for each topic (*i.e.*, the ten largest $\omega_{v,k}$ for each topic

[11] We do not report the least-concerning articles as many of the articles have a concern score of zero, thus lacking any apparent ranking.

[12] Hansen, McMahon, and Prat (2018), Larsen and Thorsrud (2017), and Larsen (2017) estimate latent topics using the popular Latent Dirichlet Allocation (LDA) model of Blei, Ng, and Jordan (2003). The LDA model, however, does not account for the possible correlation between topics. We find that allowing for non-zero correlation with the CTM model generates more coherent topics.

k). We also organize the topics into eight clusters that constitute more general themes to ease results interpretation; see Appendix A for details. From these clusters, we see that the climate change discussion in the news media is spread around several themes, which we label as: (i) "Financial and Regulation", (ii) "Agreement and Summit", (iii) "Societal Impact", (iv) "Research", (v) "Disaster", (vi) "Environmental Impact", (vii) "Agricultural Impact", and (viii) "Other."

[Insert Table 4 about here.]

To better understand how much attention media give to these topics over time, we compute the number of monthly article-equivalents for each topic. This quantity measures the hypothetical number of news articles uniquely discussing a specific topic for a given period. Formally, the number of article-equivalenst between dates τ_1 and τ_2 for topic k is defined as $\sum_{\tau=\tau_1}^{\tau_2} \sum_{s=1}^{S} \sum_{n=1}^{N_{\tau,s}} \theta_{k,n,\tau,s}$. We then aggregate the number of article-equivalents by theme.

In Figure 2, we display the monthly number of article-equivalents for each theme over the period from January 2010 to June 2018. The most discussed themes by the media, in decreasing order, are: "Financial and Regulation", "Agreement and Summit", "Societal Impact", "Research", "Disaster", "Environmental", and "Agricultural Impact". We observe significant time variations in the percentage of coverage attributed to the themes. For instance, the "Agreement and Summit" theme tends to have a larger number of article-equivalents during months where there are notable conferences on climate change. Similarly, we observe an increase in the "Disaster" theme in 2012 and 2017. These spikes are related to very destructive wildfire seasons. The time variation of newspapers' coverage of themes implies that each topic captures different dimensions of the climate change discussion.

[Insert Figure 2 about here.]

3.2. S&P 500 stock universe and their greenhouse gas emission intensity

Our analyses require the identification of green and brown firms. We define green (brown) firms as firms that create economic value while (not) minimizing damages to the environment and particularly damages that contribute to climate change. To quantify the damages to the environment, we use the greenhouse gas (GHG) emission level disclosed by the firms. We retrieve these variables from the Asset4/Refinitiv database. Similarly to Ilhan, Sautner, and Vilkov (2020), we focus on S&P 500 firms because surveys on greenhouse gas emissions typically target these. Thus we can assume an accurate level of reporting.[13]

The greenhouse gas 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 the firm's value chain. These are reported in tonnes of carbon dioxide (CO2) equivalents. We focus on the total GHG emission level defined as the sum of the three variables. To account for the economic value generated by the firm's GHG emissions, we scale the total GHG emissions by the firm's annual revenue. The revenue is obtained from the Compustat database. Whether a firm classifies as green or brown will depend on its position within the firms' distribution of the total tonnes of CO2-equivalent GHG emissions attributed to a one million dollars revenue. This scaled-GHG variable is refered to as GHG emissions intensity (see Drempetic, Klein, and Zwergel 2019; Ilhan, Sautner, and Vilkov 2020).[14]

In Table 3, we report the percentage of firms in the S&P 500 universe with available GHG emissions (Panel A) and the summary statistics of the GHG emissions intensity

[13]Our results and conclusions are robust when considering S&P 1500 firms. However, beyond the S&P 500 universe, few firms disclose their greenhouse gas emissions.

[14]The environmental dimension in ESG scoring is an alternative variable to classify firms in the green to brown spectrum. However, Drempetic, Klein, and Zwergel (2019) suggest that these scores do not reflect the sustainability of firms adequately. Additionally, Berg, Koelbel, and Rigobon (2019) show that the correlations between the ESG scores of different data providers are weak, indicating a lack of reliable and consistent scoring methodology across providers.

(Panel B). While our GHG emissions source differs from Ilhan, Sautner, and Vilkov (2020) who use the Carbon Disclosure Project database, we see that our coverage of S&P 500 firms is similar, averaging slightly above 50% of the firms in the universe. The average GHG emission is 682.49 tonnes of CO2-equivalent emissions by one million revenue. The 25th and 75th percentiles are 21.54 and 378.93, respectively. The quartiles, together with the skewness and kurtosis statistics, indicate a distribution of GHG emissions intensity that is highly positively skewed and fat-tailed.

[Insert Table 3 about here.]

Finally, we note that GHG emissions are typically reported with a one-year delay. Similarly to Ilhan, Sautner, and Vilkov (2020), we account for this by shifting the GHG emission intensity variable by twelve months in our analyses.

4. Results

Below, we test whether we can capture the unexpected increases in climate change concerns using media information, and whether green firms' stock returns are higher than brown firms' stock return in case of unexpected increases in climate change concerns.

4.1. Climate change concerns index

Using the methodology presented in Section 2 and the data of Section 3, we build the MCCC index. We compute the source-specific standard deviation σ_s necessary to obtain the standardized source-specific media climate change concern with the news media articles published from 2003 to 2009. Then, we aggregate the resulting source-specific indices to obtain the MCCC index for the 2010-2018 period. In Figure 1, we display the daily evolution of the index from 2003-2018, noting that the 2003-2009 period is forward-looking and not used in the main analysis, but is still of interest for the validation of the index. We interpret the daily index as a proxy for unexpected increases in climate change concerns. We also display a 30-day moving average of the index to help identify trends and events.[15]

[Insert Figure 1 about here.]

First, we see that the index's spikes correspond to climate change events, such as the 2012 Doha UN Climate Chance Conference or the Paris Agreement. We also note that climate change concerns, proxied by the moving average, exhibit cycles of low and high values. A first high climate change concerns period is observed following the 2007 United Nations (UN) Security Council talks on climate change and lasts until the beginning of 2010, after the Copenhagen UN Climate Change Conference. The second high 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 days when U.S. President Donald Trump announced the U.S. withdrawal from the Paris Agreement. These observations suggest that our index captures meaningful events that, we posit, correlate with real latent unexpected increases in climate change concerns.

4.2. Climate change concerns as a factor explaining GMB portfolio returns: A conditional mean analysis

Our first analysis focuses on the average return of the green minus brown (GMB) portfolio conditional on the MCCC index's value. To build our GMB portfolio, we divide the assets into three groups: green, neutral, and brown. Green (brown) stocks are firms for which the GHG emissions intensity variable belongs to the lowest (highest) quartile of all firms values at time t. Neutral firms are the remainder. We then build equal-weighted green and brown portfolios and a long-short GMB portfolio.[16]

We use percentiles of the MCCC index over the 2010-2018 period as thresholds for the conditioning variable. In Figure 3, we display the average performance of the GMB

[15]This moving average can be interpreted as a proxy for the real level of climate change concerns. This interpretation requires the assumption that concern about climate change concerns only decreases because of the effect of time and that news published more than 30 days ago does not have an effect on the current climate change concerns.

[16]Results are qualitatively similar using market-capitalization-weighted portfolios.

portfolio conditional on the thresholds. We see a clear positive relationship between the average return and the MCCC threshold. In particular, when the MCCC index is above its 85th percentile, we notice a large increase in the GMB average return. Moreover, the average GMB portfolio return is always higher when the MCCC is above the thresholds. These preliminary findings are consistent with the idea that green firms outperform brown firms when there is an unexpectedly high increase in climate change concerns.

[Insert Figure 3 about here.]

4.3. Climate change concern as a factor explaining GMB portfolio returns: A multivariate factor analysis

We now consider a multivariate linear regression framework to control for other factors potentially driving stock returns. We regress the green, brown, and GMB portfolios' excess returns on the MCCC index and common factors used in the financial literature. As factors, we consider the five Fama-French factors (Fama and French 2015), *i.e.*, (i) *MKT*, the excess market return, (ii) *SMB*, the small minus big factor, (iii) *HML*, the high minus low factor, (iv) *RMW*, the robust minus weak factor, and (v) *CMA*, the conservative minus aggressive factor. We also include (vi) *MOM*, the momentum factor of Carhart (1997). This yields the following specification:

$$\begin{aligned} r_{p,t} = c_p + \beta_p^{MCCC} MCCC_t + \beta_p^{MKT} MKT_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t \\ + \beta_p^{RMW} RMW_t + \beta_p^{CMA} CMA_t + \beta_p^{MOM} MOM_t + \varepsilon_{p,t} \,, \end{aligned} \tag{6}$$

where $r_{p,t}$ is the excess return of the portfolio (*i.e.*., green, brown, or GMB), c_p is a constant, $\beta_p^{\bullet}$ are regression coefficients, and $\varepsilon_{p,t}$ is an error term. Given our second hypothesis, we expect that $\beta_G^{MCCC} > 0$, $\beta_B^{MCCC} < 0$, and $\beta_{GMB}^{MCCC} > 0$, where G stands for green, B for brown, and GMB for green minus brown.

Estimation results are reported in Table 5. First, let us consider the GMB portfolio. In this case, we see that the MCCC index's estimated regression coefficients align with our hypothesis. Specifically, a one-unit increase in the MCCC index implies an additional daily positive return of 7.5 basis point. This effect is highly significant with the t-stat at about 3.2, above the significance hurdle of 3.0 proposed by Harvey, Liu, and Zhu (2016). The estimated coefficients indicate that the GMB portfolio is positively related to *MKT*, *HML*, *SMB*, and *MOM* and negatively related to *CMA* and *RMW*. Thus, the GMB portfolio loads more on large firms with lower growth, aggressive investment policies, and weak operating profits. The *CMA* coefficient is large at -0.639 compared to the other coefficients. This finding is consistent with the idea that green firms' capital investment costs are higher than the ones of brown firms, which we posit is because green technologies and solutions are less mature than brown ones.

[Insert Table 5 about here.]

Looking at the green portfolio, we find a positive and highly significant exposure to the MCCC index. For the brown portfolio, we find a highly significant negative coefficient. Moreover, we find that the *MCCC* coefficient for the brown portfolio is larger in absolute value than for the green portfolio. This finding implies that the investors' strategy on sustainability tends towards a negative screening of brown firms, as opposed to the reallocation of brown investment capital to green investment capital (see Verheyden, Eccles, and Feiner (2016) and Henke (2016) for analyses of sustainability screening methods). The coefficients associated with the other factors are as for the GMB portfolio. In particular, the *CMA* coefficient for the green portfolio is negative, and the brown portfolios' coefficient is positive, indicating that green firms invest aggressively, while brown firms do not.

4.4. Climate change concerns in the cross-section of stock returns

In the previous section, we find that the stock returns of a portfolio of firms with high (low) GHG emissions intensity are positively (negatively) associated with unexpected increases in climate change concerns. We now test if we can recover this relationship using stock-level return exposures to the MCCC index. To do so, we define the following panel regression:

$$r_{i,t} = c + \gamma^{GHG} \log(GHG_{i,t}) + \gamma^{MCCC} \log(GHG_{i,t}) MCCC_t + \boldsymbol{\beta}_i \mathbf{CTRL}_t + \epsilon_{i,t} \,, \qquad (7)$$

where $r_{i,t}$ is the stock return of firm i at time t and $\mathbf{CTRL}_t$ are control factors. We consider a one-factor (*MKT*), three-factor (*MKT*, *HML*, *SMB*), and a six-factor (*MKT*, *HML*, *SMB*, *RMW*, *CMA*, *MOM*) specification. Here, coefficients $\gamma^{\bullet}$ are common to all firms while $\beta_{\bullet}$ coefficients are firm-specific.[17] Finally, we standardize $\log(GHG_{i,t})$ in the cross-section at each day t to focus on the cross-sectional variations between firms.

In specification (7), the exposure of firms to the Media Climate Change Concerns is a function of their log GHG emissions intensity. Thus, we expect a significant negative value of γ^{MCCC}, so that the higher the level of GHG emissions intensity, the more negative the exposure to unexpected increases in climate change concerns, in line with the Pastor, Stambaugh, and Taylor (2020) prediction. We also expect a positive and significant value of γ^{GHG}. We base this expectation on the idea that owning brown firms provides disutility to investors. Therefore, investors require a higher return rate as compensation, which is a core assumption of the model of Pastor, Stambaugh, and Taylor (2020). On the other side, owning green firms provides utility to investors, thus requiring a lower return rate.

Panel regression results are reported in Table 6. For all specifications, we find γ^{MCCC} to be negative and highly significant, in line with our expectations. The coefficient implies that firms with a one standard deviation log GHG emissions intensity above the cross-sectional mean have negative exposures to climate concern of -0.033. Moreover, γ^{GHG} is highly significant and positive in all specifications, thus consistent with the hypothesis that brown firms provide a higher return rate than green firms in the long-run. This result implies that a firm with a one standard deviation log GHG emissions intensity above the cross-sectional mean has an additional daily return of 1.7 basis point on average. Thus,

[17] In addition, we considered a firm fixed-effect specification where c is replaced by c_i as well as a threshold model in which regression parameters are conditioned on the value of *MCCC* being above or below a certain threshold calibrated with AIC (Akaike 1973). Conclusions remained unchanged.

according to the estimated coefficients, green firms' stock returns are higher than brown firms' stock returns above approximately a level MCCC of 0.51, which is about 48% of the observations from 2010-2018.[18] The vast majority of the observations above this level are for years from 2014 to 2017.

[Insert Table 6 about here.]

As an alternative test, we consider a multivariate Fama-Macbeth cross-sectional regression framework (Fama and MacBeth 1973):

$$r_{i,t} = c_t + \lambda_t^{GHG} \log(GHG_{i,t}) + \boldsymbol{\lambda}_t \mathbf{CTRL}_{i,t} + \epsilon_{i,t}\,, \tag{8}$$

where our focus is now on λ_t^{GHG}. λ_t^{GHG} represent the effect of GHG emissions intensity on stock returns at each point in time. Thus, if λ_t^{GHG} is positive (negative), brown firms have a higher (lower) return than green firms at time t controlling for other firms' characteristics considered in $\mathbf{CTRL}_{i,t}$. We can capture the contemporaneous relationship between that GHG emissions intensity effect and the MCCC index as follows:

$$\lambda_t^{GHG} = c + \beta MCCC_t + \eta_t\,. \tag{9}$$

Under the model of Pastor, Stambaugh, and Taylor (2020), returns of high (low) GHG emissions intensity firms are lower (higher) when MCCC is high. Thus, we expect β to be negative.

We consider several firms' characteristics in the controls $\mathbf{CTRL}_{i,t}$: the stock's market beta, size, and book-to-market (Fama and French 1992), the momentum and reversal (Jegadeesh and Titman 1993), the stock's monthly co-skewness (Harvey and Siddique 2000), the stock's illiquidity measure (Amihud 2002), the idiosyncratic volatility and stock exposure to aggregate stock market volatility (Ang, Hodrick, Xing, and Zhang 2006), the annual growth rate of total asset and quarterly return on equity (Hou, Xue, and Zhang

[18] We note that from 2003-2009, where GHG data availability is more scarses, this corresponds to only 28% of the observations.

2015), and the lottery-like stock characteristic (Bali, Cakici, and Whitelaw 2011). We refer the reader to Bali, Brown, and Tang (2017) for details on the computation of these variables. We first proceed by estimating λ_t^{GHG} in (8) cross-sectionally every day using various sets of control characteristics.

In Table 7, we report the estimations of the β in (9) for the various specifications in the control characteristics. For all cases, we find a negative and significant coefficient λ_t^{GHG}, consistent with the hypothesis that the stock returns of brown (green) firms is reduced (increased) when there are unexpected increases in climate change concerns.

Overall, with the above analyses, we find strong evidence that green versus brown firms' stock return performance is related to the unexpected increases in climate change concerns. Furthermore, the panel regression results indicate that brown firms tend to outperform green firms when the Media Climate Change Concern is low enough. These results are all consistent with the model of sustainable investing by Pastor, Stambaugh, and Taylor (2020).

[Insert Table 7 about here.]

5. Dimensions of climate change concerns

So far, we have established a relationship between unexpected increases in climate change concerns, proxied by the Media Climate Change Concerns index, and returns of green versus brown firms. However, climate change is a broad subject and can be related to many other topics, such as disasters, financial impacts, environmental impacts, or regulatory impacts. Engle, Giglio, Kelly, Lee, and Stroebel (2020) suggest analyzing whether news about physical damages from climate change and news about regulatory risks have a different impact on stock returns. Moreover, the model of Pastor, Stambaugh, and Taylor (2020) implies that the effect of climate change concerns arises from two channels: (i) the expected cash-flow channel and (ii) the investors' taste channel. Below, we build topical indices of media climate change concerns and analyze which dimension drives the relationship between unexpected increases in climate change concerns and green versus brown stock returns. We then try to associate these subjects to the cash-flow and/or to the taste channel.

5.1. *Topical climate change concerns and the stock market*

To build the topical MCCC indices, we consider a topic-attribution weighted version of (2):

$$concern_{k,t,s} = \sum_{n=1}^{N_{t,s}} \theta_{k,n,t,s} concern_{n,t,s} \,, \tag{10}$$

where $\theta_{k,n,t,s}$ is obtained from the estimated CTM. We normalize and aggregate the scores per indices, following the steps of Section 2.2. This yields $K = 40$ topical MCCC indices, which we denote by $MCCC_{k,t}$.[19]

To identify which themes and which topics drive the relationship between climate change concerns and stock returns, we reconsider the approach of Section 4.3 with the following specification:

$$\begin{aligned} r_{p,t} = \alpha_p + \beta_{k,p}^{MCCC} MCCC_{k,t} + \beta_p^{MKT} MKT_t + \beta_p^{SMB} SMB_t + \beta_p^{HML} HML_t \\ + \beta_p^{RMW} RMW_t + \beta_p^{CMA} CMA_t + \beta_p^{MOM} MOM_t + \epsilon_{p,t} \,. \end{aligned} \tag{11}$$

The quantities of interest are now $\beta_{k,p}^{MCCC}$ as opposed to β_p^{MCCC}.[20]

Regression results are reported in Table 8. First, we find that not all topics influence green versus brown firms' stock returns. Out of the 40 topics, only 22 report a significant coefficient, albeit, for all topics, the sign of the relationship is in line with our hypothesis, that is, positive for the GMB and green portfolio, and negative for the brown portfolio. Also, consistent with our previous results, the brown portfolio coefficients in all cases are higher, in absolute value, than the green portfolio coefficients.

[Insert Table 8 about here.]

[19] The MCCC index is obtained as a special case of (10) by setting $\theta_{k,n,t,s} = 1 \; \forall \; n, t, s$.

[20] The panel specification and Fama-MacBeth cross-sectional specification presented in Section 4.4 lead to the same conclusion than (11).

Summarizing the results by theme, we find that “Financial and Regulation”, “Agreement and Summit”, “Societal Impact”, “Research”, and “Disaster” contain multiple topics with significant coefficients. Given the financial nature of the topics in “Financial and Regulation”, we posit that the theme affects the cash-flow channel primarily. On the other hand, “Research” is likely to affect the taste channel only as research results hardly impact firms’ cash-flows, at least in the short-term. The theme “Agreement and Summit” is likely to affect both channels. On the one hand, regulations can have direct impacts on firms’ future cash flows. On the other hand, the discussions taking place at these conferences often underline the future disastrous consequences of climate change, which can affect the taste channel of investors. For “Societal Impact”, we posit the theme is likely to affect the taste channel. However, because of Topic 30, which discusses green programs’ fundings, the public impact theme could also affect the cash-flow channel through subventions to green firms and green projects. Finally, we believe “Disaster” affects the taste channel primarily by exposing the population to the direct impact of climate change if strong actions are not taken.

6. Conclusion

Our paper empirically verifies the prediction of Pastor, Stambaugh, and Taylor (2020) that green firms can outperform brown firms when climate change concerns strengthen unexpectedly.

Our first contribution is to construct a daily proxy to capture unexpected increases in climate change concerns at the daily frequency. To do so, we collect all the news articles published about climate change from the most circulated U.S. newspapers over the period 2003-2018. We then design an article-level concern score and aggregate these scores daily across newspapers to obtain our Media Climate Change Concerns index. We find that this index captures several key climate change events that are highly susceptible to increase concerns about climate change.

Our second contribution is to show the impact of the climate change concern index on the difference in performance between green (resp. brown) stocks based on their greenhouse gas emissions intensity from 2010 to 2018. Multiple analysis leads to the same conclusion: Green firms outperform brown firms when there is a sufficiently high value in the Media Climate Change Concerns index. This result also implies that brown firms outperform green ones at a low value of the index. We also document that brown stocks are more impacted by climate change concerns than green stocks, supporting the idea that investors use screening methodologies to disinvest in brown stock and to reinvest in the rest of the market, and not only in green stocks.

Finally, we derive topical Climate Change Concern indices to evaluate the suggestion by Pastor, Stambaugh, and Taylor (2020) that the effect arises from a cash-flow channel and an investors' taste channel. To do so, we divide the news article corpus into sets of topics using a correlated topic model. Our analysis identifies a set of eight themes (*i.e.*, cluster of topics), from which five contain topical indices with a significant relationship with the stock returns of green vs. brown stocks. Our results suggest that some of the topics with significant relationship to the green vs. brown stock returns can only be rationalized to affect the cash-flow channel. In contrast, others cannot, and thus affect the taste channel. Thus, we empirically validate the idea that the effect arises from a cash-flow channel and a investors' taste channel.

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Table 1: Sources of climate change news

This table reports the name of the source, the number of articles discussing climate change, the total number of articles published, and the percentage of climate change articles. The time period ranges from January 2003 to June 2018.

Source	Climate	Total	%
The Wall Street Journal	3,776	1,673,007	0.23
The New York Times	3,711	1,477,936	0.25
The Washington Post	2,323	1,029,917	0.23
The Los Angeles Times	1,594	747,557	0.21
The Chicago Tribune	509	1,058,643	0.05
USA Today	249	149,450	0.17
The New York Daily News	129	220,002	0.06
The New York Post	109	190,880	0.06

Table 2: Most concerning climate change news articles

This table reports the most concerning news articles according to our article-level concern score. We report the publication date, the concern score, the negativity level, the level of risk, the first 50 characters of the article's title, and the source. The weight is defined as the level of risk times the level of negativity. The level of negativity and risk are computed using the LIWC2015 sentiment and risk lexicons.

Rank	Date	Concern	Risk	Negativity	Title	Source
1	2014-06-25	4.80	5.48	0.88	Warning on biz 'climate'	The New York Daily News
2	2018-01-05	3.44	3.98	0.87	Storms, Fires and Floods Lead to Record Payouts	The New York Times
3	2018-01-04	3.44	3.98	0.86	2017 Set a Record for Losses From Natural Disaster	The New York Times
4	2010-03-12	3.04	3.04	1.00	The Climate Rules Weren't From Us	The Wall Street Journal
5	2018-02-05	3.02	3.92	0.77	An urgent national security issue	The Washington Post
6	2010-03-13	2.93	2.93	1.00	The Climate Rules Weren't From Us	The Wall Street Journal
7	2011-12-08	2.89	3.55	0.82	2011 saw record number of high-cost weather disast	The Los Angeles Times
8	2017-02-22	2.79	4.19	0.67	Questions for: 'Mexico City, Parched and Sinking,	The New York Times
9	2011-12-09	2.77	3.69	0.75	A dozen billion-dollar weather disasters in 2011	The Chicago Tribune
10	2018-06-23	2.76	3.45	0.80	Picturing climate change	The Washington Post
11	2008-10-07	2.73	2.88	0.95	One in 4 Mammals Threatened With Extinction, Group	The New York Times
12	2015-05-21	2.72	5.07	0.54	Global warming is risk to security, Obama says	The Chicago Tribune
13	2005-03-12	2.66	3.30	0.81	'I Have a Nightmare'	The New York Times
14	2014-10-22	2.63	3.47	0.76	A Retreat From Weather Disasters	The New York Times
15	2008-01-03	2.60	3.85	0.67	Disasters the 'new normal'	USA Today
16	2016-06-19	2.59	3.46	0.75	EMP: More Urgent Than Any Climate Threat; It is in	The Wall Street Journal
17	2018-01-26	2.59	3.15	0.82	Doomsday Clock moves 30 seconds ahead, landing at	The Washington Post
18	2014-04-06	2.57	3.80	0.68	The perils of climate change	The Washington Post
19	2017-08-08	2.56	3.96	0.65	Don't Ignore the Dire Threat of Climate Change	The New York Times
20	2017-08-09	2.55	3.94	0.65	Don't Ignore the Dire Threat of Climate Change	The New York Times

Table 3: Summary statistics of the revenue-scaled greenhouse gas emissions variable
This table reports summary statistics of the revenue-scaled greenhouse gas emissions level used to establish firms' greenness and brownness. Panel A reports for each year the percentage of firms with available greenhouse gas emissions data in the S&P 500 universe. Panel B reports summary statistics: the total number of observations, the average, the standard deviation, the minimum, the 25th percentile, the median, the 75th percentile, and the maximum.

Panel A: Percentage of firms with emissions data	
Year	*GHG*
2009	52.27
2010	57.44
2011	62.92
2012	64.73
2013	58.61
2014	57.30
2015	56.50
2016	60.27
2017	60.14
Panel B: Summary statistics	
Statistics	*GHG*
Observations	2,429
Average	680.57
Standard deviation	1,584.01
Skewness	3.22
Kurtosis	10.74
Minimum	1.10
25th percentile	21.41
50th percentile	59.52
75th percentile	368.41
Maximum	9,445.71

Table 4: Highest probability words for each topic

This table reports, for each topic k, the words with the ten highest probability $\omega_{v,k}$. The topics are estimated using the Correlated Topic Model. We estimate $K = 40$ topics. For ease of interpretation, we split the topics into eight themes.

Topic	1	2	3	4	5	6	7	8	9	10	Theme
Topic 40	project	technology	plant	cost	coal	carbon_dioxide	power_plant	facility	scale	carbon	Financial and Regulation
Topic 32	car	vehicle	standard	truck	automaker	diesel	emission	auto	engine	fuel	Financial and Regulation
Topic 31	oil	tax	fuel	price	carbon_tax	production	taxis	cost	ethanol	revenue	Financial and Regulation
Topic 25	home	business	product	consumer	building	panel	energy_efficiency	customer	bulb	light	Financial and Regulation
Topic 21	market	industry	emission	permit	credit	system	allowance	cap	price	cost	Financial and Regulation
Topic 17	investor	investment	business	executive	risk	firm	fund	bank	shareholder	asset	Financial and Regulation
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Topic 18	agreement	deal	talk	meeting	commitment	conference	target	accord	treaty	official	Agreement and Summit
Topic 14	email	science	document	headline	information	investigation	research	letter	statement	committee	Agreement and Summit
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Topic 34	poll	survey	majority	public	pew	penguin	concern	opinion	result	support	Public Impact
Topic 30	money	program	budget	development	fund	funding	effort	initiative	aid	poverty	Public Impact
Topic 11	child	school	student	family	woman	life	street	art	event	police	Public Impact
Topic 9	health	death	disease	security	population	threat	child	life	war	risk	Public Impact
Topic 8	science	book	story	truth	film	news	movie	medium	reader	life	Public Impact
Topic 22	earth	atmosphere	planet	space	cloud	science	satellite	system	research	sun	Research
Topic 5	study	researcher	temperature	research	paper	finding	effect	change	author	activity	Research
Topic 3	datum	temperature	model	trend	record	estimate	period	figure	increase	rate	Research
Topic 36	weather	storm	hurricane	record	temperature	event	heat	heat_wave	drought	wind	Disaster
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Topic 12	island	sea	sea_level	storm	flood	flooding	land	beach	home	village	Disaster
Topic 39	ice	glacier	snow	ice_sheet	ocean	temperature	sea_level	satellite	mountain	researcher	Environmental Impact
Topic 29	team	researcher	lake	rock	period	study	layer	sample	evidence	eruption	Environmental Impact
Topic 28	forest	tree	land	deforestation	carbon	plant	wood	soil	rain_forest	pine	Environmental Impact
Topic 10	specie	bird	park	habitat	animal	wildlife	conservation	population	extinction	plant	Environmental Impact
Topic 1	ship	drilling	oil	sea	fishing	shipping	coast	boat	shell	exploration	Environmental Impact
Topic 23	farmer	crop	farm	agriculture	plant	soil	corn	rice	land	wheat	Agricultural Impact
Topic 20	food	animal	meat	cow	cattle	farm	ski	resort	beef	diet	Agricultural Impact
Topic 4	drought	region	river	rain	desert	lake	dam	rainfall	water_supply	mountain	Agricultural Impact
Topic 2	wine	grape	coffee	region	fruit	vineyard	temperature	sugar	bottle	harvest	Agricultural Impact
Topic 27	bear	permafrost	ice	sea_ice	population	seal	species	hunting	animal	wildlife	Other
Topic 26	reef	ocean	coral	algae	fish	barrier_reef	sea	ecosystem	acidification	tourism	Other

Probability: 0.05, 0.10

Table 5: Regression results of portfolios' returns and the MCCC index

This table reports the results of the regression of the daily MCCC index and control factors on the GMG, green, and brown portfolios' returns. The constituents of those portfolios are based on their yearly revenue-scaled GHG emissions. The model is estimated with data ranging from January 2010 to June 2018. Newey and West (1987, 1994) standard errors or the estimators are reported in parentheses. The signs *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	GMB	Green	Brown
Intercept	−0.035*	−0.011*	0.025*
	(0.018)	(0.008)	(0.013)
MCCC	0.075***	0.028***	−0.056***
	(0.024)	(0.011)	(0.018)
MKT	0.159***	1.106***	0.965***
	(0.017)	(0.007)	(0.012)
HML	0.169***	0.175***	0.031***
	(0.046)	(0.023)	(0.030)
SMB	0.119***	0.018***	−0.109***
	(0.034)	(0.013)	(0.028)
CMA	−0.558***	−0.091***	0.439***
	(0.063)	(0.034)	(0.045)
RMW	−0.207***	−0.138***	0.121***
	(0.049)	(0.019)	(0.039)
MOM	0.130***	−0.063***	−0.182***
	(0.028)	(0.013)	(0.020)

Table 6: Panel regressions results of individual firms' returns

This table reports panel regressions results about the effect of logarithm of the revenue-scaled GHG emissions (intensity) on the stock-level exposure to the MCCC index; see (7). The regression is estimated on S&P 500 firms data from the period ranging from January 2010 to June 2018. We report the intercept and the exposure to $\log(GHG)$ (*i.e.*, λ^{GHG}) and to $\log(GHG) \times MCCC$ (*i.e.*, λ^{MCCC}). For the controls, we use a one-factor (*i.e.*, *MKT*), three-factor (*i.e.*, *MKT*, *HML*, *SMB*), and six-factor (*i.e.*, *MKT*, *HML*, *SMB*, *RMW*, *CMA*, *MOM*) model. Standard errors of the estimators are reported in parentheses. The signs *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	One-factor	Three-factor	Six-factor
Intercept	0.003^{*}	0.004^{**}	0.003^{**}
	(0.002)	(0.002)	(0.002)
$\log(GHG)$	0.017^{***}	0.016^{***}	0.013^{***}
	(0.003)	(0.003)	(0.003)
$\log(GHG) \times MCCC$	-0.033^{***}	-0.031^{***}	-0.027^{***}
	(0.004)	(0.004)	(0.004)

Table 7: Fama-MacBeth regression results

This table reports the estimated intercept and exposure of the logarithm of the GHG emissions intensity coefficient to the MCCC index; see (9). The daily GHG emissions intensity coefficient is first estimated by running, every day, a cross-sectional regression, controlling for firm-level characteristics; see (8). We consider six specifications, each consisting of various sets of firm-characteristic variables for the controls: Specification (1) does not include any controls, (2) includes the market beta characteristic, (3) extends the set in (2) to control for the exposure to the aggregate volatility, (4) extends the set in (3) to control for the size, the book-to-market, and the momentum characteristics, (5) extends (4) to control for the reversal, the illiquidity, the coskewness, the idiosyncratic volatility, the annual growth on assets, and the return on equity characteristics. Finally, (6) extends (5) with the lottery-like characteristic. We refer to Bali, Brown, and Tang (2017) for details on how to construct the characteristics. Newey and West (1987, 1994) standard errors of the estimators are reported in parentheses. The signs *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.006	0.005	0.005	0.003	0.003	0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MCCC	-0.016^{***}	-0.014^{***}	-0.013^{***}	-0.011^{**}	-0.009^{**}	-0.008^{**}
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)

Table 8: Regression results of portfolios' returns and the topical MCCC indices
This table reports the estimates of $\beta_{k,p}^{MCCC}$ in the regression of topical daily MCCC indices on the GMB, green, and brown portfolios; see (11). Row indicates on which topic the MCCC index is based while the columns indicate on which portfolio's returns the analysis is performed. The signs *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively. They are obtained via t-stats for which the standard error of the estimator is estimated using Newey and West (1987, 1994). The regressions are estimated with data for the period ranging from January 2010 to June 2018.

	GMB	Green	Brown
Theme "Financial and Regulation"			
Topic 40	0.085**	0.036**	−0.043**
Topic 32	0.054*	0.038*	−0.038*
Topic 31	0.076**	0.033**	−0.044**
Topic 25	0.074**	0.032**	−0.059**
Topic 21	0.127***	0.055***	−0.075***
Topic 17	0.053*	0.018*	−0.036*
Topic 16	0.081***	0.028***	−0.052***
Topic 15	0.066**	0.026**	−0.038**
Topic 13	0.024	0.023	−0.007
Topic 7	0.090***	0.048***	−0.063***
Topic 6	0.039	0.013	−0.036
Theme "Agreement and Summit"			
Topic 37	0.063***	0.022***	−0.048***
Topic 35	0.049**	0.013**	−0.039**
Topic 19	0.027*	0.005*	−0.021*
Topic 18	0.107***	0.034***	−0.072***
Topic 14	0.041	0.012	−0.029
Theme "Public Impact"			
Topic 38	0.062**	0.026**	−0.043**
Topic 34	0.061**	0.021**	−0.036**
Topic 30	0.087***	0.030***	−0.059***
Topic 11	0.047*	0.024*	−0.038*
Topic 9	0.032	0.025	−0.020
Topic 8	0.036	0.013	−0.030
Theme "Research"			
Topic 22	0.100***	0.051***	−0.056***
Topic 5	0.044*	0.029*	−0.022*
Topic 3	0.073**	0.038**	−0.044**
Theme "Disaster"			
Topic 36	0.026	0.01	−0.013
Topic 33	0.052**	0.011**	−0.038**
Topic 24	0.035	0.016	−0.028
Topic 12	0.048*	0.019*	−0.036*
Theme "Environmental Impact"			
Topic 39	0.017	0.013	−0.015
Topic 29	0.048	0.023	−0.043
Topic 28	0.073*	0.043*	−0.067*
Topic 10	0.046	0.016	−0.031
Topic 1	0.033	0.019	−0.015
Theme "Agricultural Impact"			
Topic 23	0.007	0.011	0.000
Topic 20	0.007	0.005	−0.007
Topic 4	0.033	0.016	−0.028
Topic 2	0.007	0.007	−0.008
Theme "Other"			
Topic 27	0.055	0.017	−0.048
Topic 26	0.021	0.018	−0.004

Figure 1: Media Climate Change Concerns index

This figure displays the daily MCCC index (gray points) together with its 30-day moving average (bold line). We also report several major events related to climate change (in boxes). The period ranges from January 2003 to June 2018. The observations before January 1, 2010 (*i.e.*, at the left of the black dotted line) are considered to be forward-looking since the data from that period is used to compute the source-specific standard deviation estimate necessary 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 our main analysis's time window.

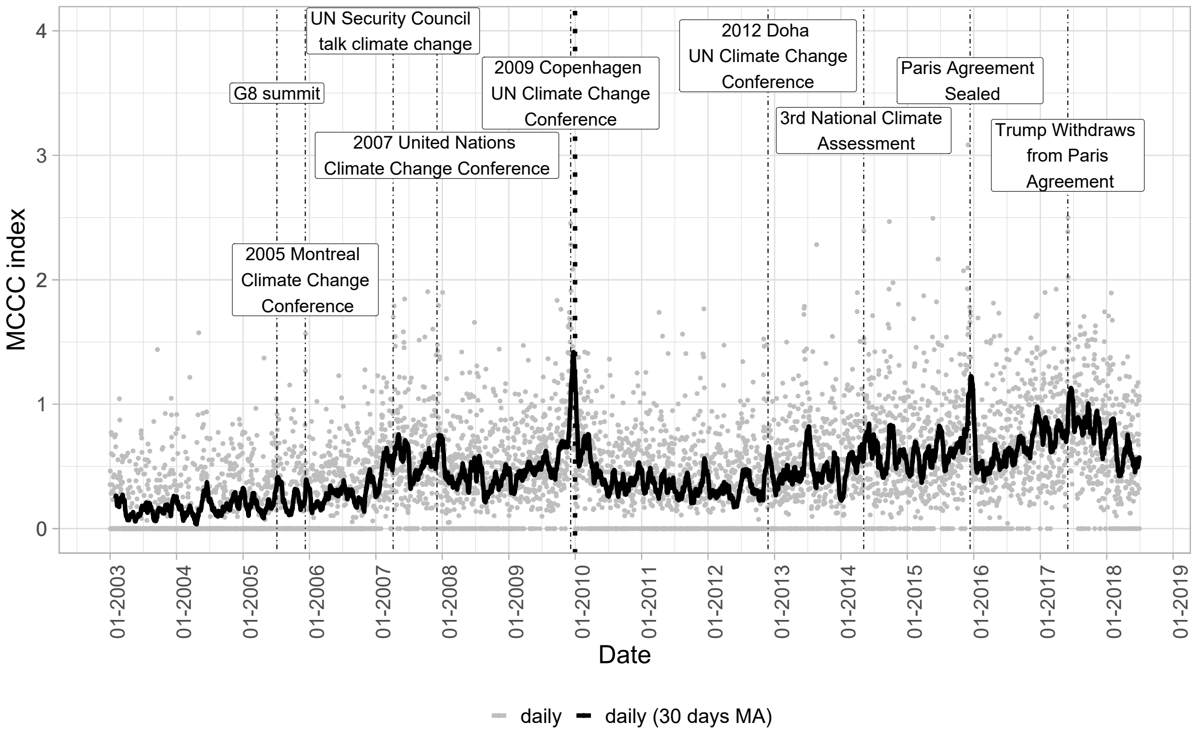


Figure 2: Monthly number of article-equivalent by theme
This figure displays the monthly number of article-equivalent publications for each theme. The time period ranges from January 2010 to June 2018.

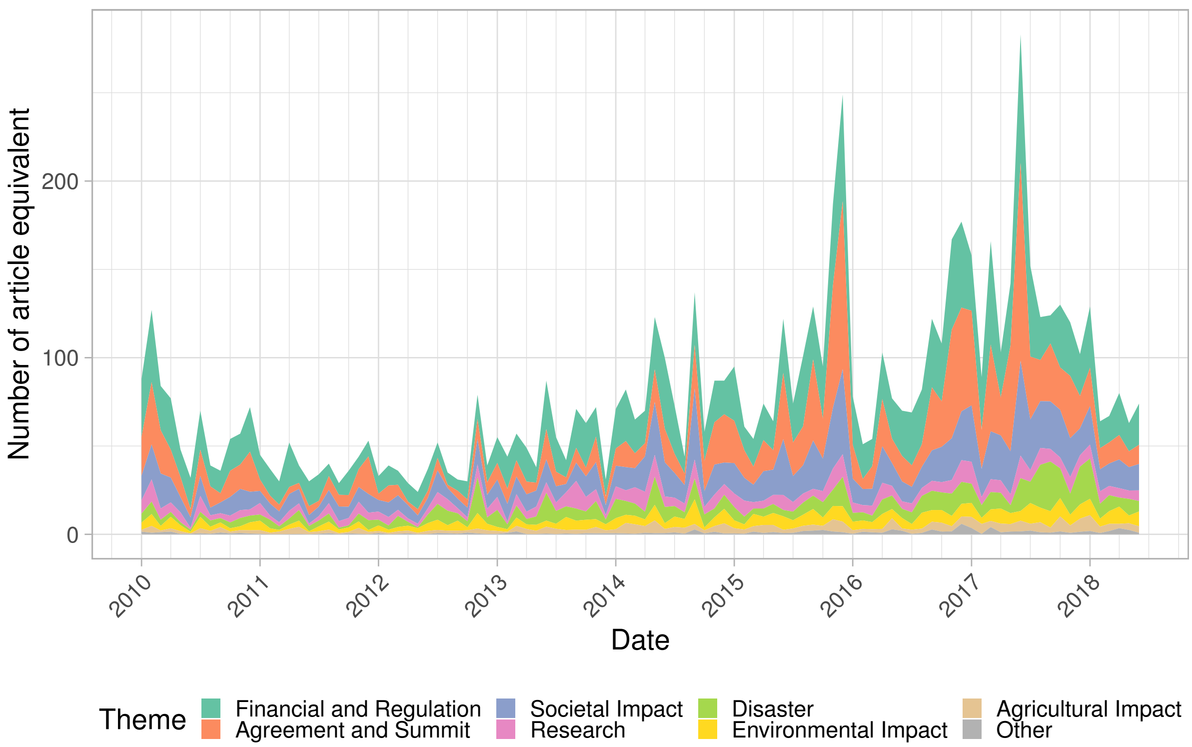
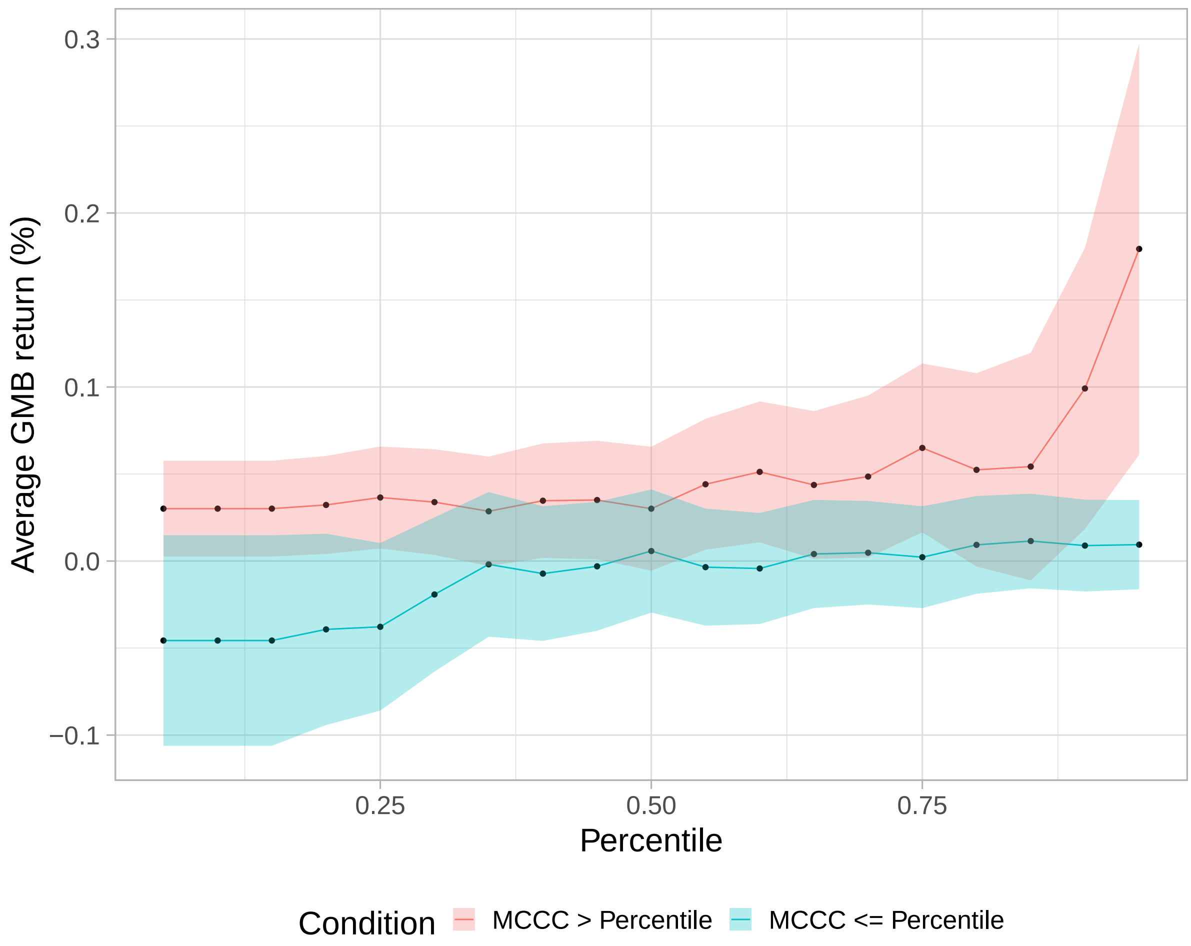


Figure 3: Green minus brown portfolio average return
This figure displays the average return of the GMB portfolio (vertical axis) conditional on the MCCC index being above or below a specific threshold (horizontal axis). Thresholds are set as percentiles of the MCCC index. The colored bands report the 95% confidence interval.



Appendix A. Topic modeling and theme construction

To improve the estimation of the topic model, we follow the recommendation of Martin and Johnson (2015) and include only nouns and proper nouns in our vocabulary of words. Moreover, following Hansen, McMahon, and Prat (2018), we also identify collocation, which is a sequence of words (in our case sequence of nouns or proper nouns) that have a specific meaning as a sequence. We only identify two-word sequence collocations. We then calculate the number of times these collocations appear and create a single term for the ones that appear more than 100 times in the climate change corpus. An example of such collocation is the sequence "climate change."

Next, we lemmatize every single terms (*i.e.*, not collocation), that is, with the use of vocabulary and morphological analysis of words, we remove inflectional endings and transform it to the base or dictionary form of a word. This step helps delete non-informative variations of words. We then remove rare words (*i.e.*, appear in less than 0.05% of the texts in the corpus) and common words (*i.e.*, appear in more than 50% of the texts in the corpus).

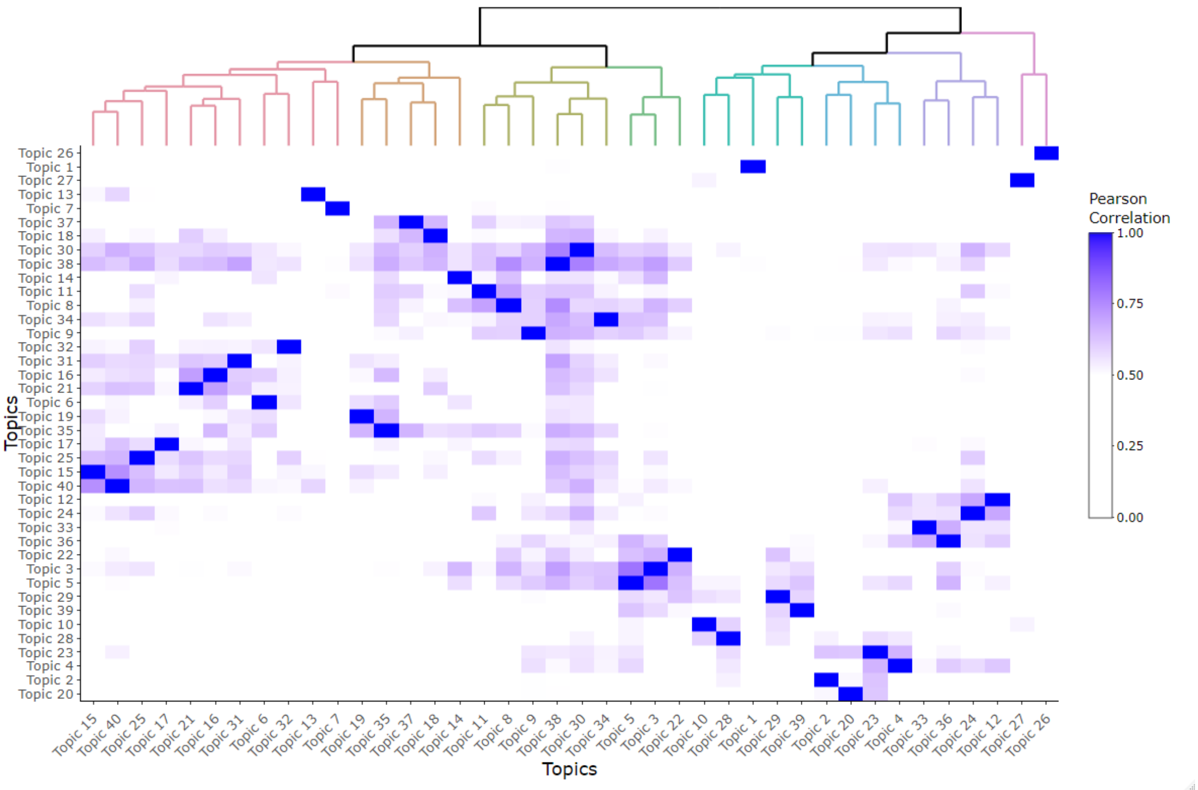
Following Hansen, McMahon, and Prat (2018), we estimate $K = 40$ topics.[21] This number of topics is a good balance between too few topics, which tends to be too general, and too much topics, which tends to be too specific. We use the R package **STM** of Roberts, Stewart, and Tingley (2014) to estimate the correlated topic model.

To construct themes, we begin by computing the correlation matrix of the topical MCCC indices. Then, we perform hierarchical clustering on this correlation matrix, where we settle on eight clusters for interpretability purposes. In Figure A.4, we display the correlation matrix as well as the dendogram generated from the hierarchical clustering algorithm, where correlations below 0.5 are kept blank for better visualization of the clusters. The correlation matrix is also reordered to put clusters side-to-side.

[Insert Figure A.4 about here.]

[21] Using the approch of Mimno and Lee (2014), we found the optimal number of topics to be 75. Hansen, McMahon, and Prat (2018) estimated the optimal number of topics to be 70 but decided to reduce this number to 40 for interpretability purposes. We follow the same reasoning here.

Figure A.4: Correlation matrix of the topical MCCC indices
This figure displays the correlation of the topical MCCC indices. The correlation matrix is rearranged according to a hierarchical clustering algorithms to highlight clusters. Correlations below the 0.5 level are kept blank. The colors in the dendrogram tree highlight the set of 8 clusters obtained with the clustering algorithm.



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Pierre Wunsch
Governor of the National Bank of Belgium

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